Machine Learning in Manufacturing Ergonomics: Recent Advances, Challenges, and Opportunities

Sujee Lee[1], *Student Member, IEEE,* Li Liu[2], Robert Radwin[1], *Senior Member, IEEE* and Jingshan Li[1], *Fellow, IEEE*

***Abstract*—The rapid development of machine learning (ML) technology has introduced substantial impact on ergonomics research in manufacturing. Numerous studies and practices have been carried out to apply ML techniques to address manufacturing ergonomics issues, which has brought extensive opportunities as well as significant challenges. To incentivize future research in this area, this paper reviews the recent advances of ML applications in manufacturing ergonomics, and discusses future research opportunities and challenges from ML, ergonomics, and manufacturing systems perspectives.**

***Index Terms*—Machine learning, ergonomics, manufacturing, opportunities, challenges**

I. INTRODUCTION

The rapid development of information and artificial intelligence (AI) technology, particularly machine learning (ML), has greatly influenced research, industry, and society. Using ML techniques for risk assessment and injury prevention represents a new trend in ergonomics research. According to Bureau of Labor Statistics, more than 30% of DAFW (days away from work) cases in the US private sector are due to musculoskeletal disorders (MSDs), i.e., ergonomic injuries, which occur when the body uses muscles, tendons, and ligaments to perform tasks, and lead to a median of 12 days away from work [1]. Thus, ergonomics, as an important part of engineering, especially for manufacturing, has attracted growing interest from ML research. The revolutionary and paradigm change due to Industry 4.0 has expedited such a trend, and generated numerous opportunities for innovations and many new challenges [2], [3]. These opportunities and challenges have significantly expanded the scope of traditional ergonomics research. Therefore, there is a need to review the recent advances and development in ML applications for ergonomics study in manufacturing, and provide strategic views of visions and directions for future research and practice. The main contribution of this paper is to present such a study from a manufacturing system perspective by focusing on integration of ML technology with ergonomics research for manufacturing applications, structured from small scale and detailed activities to large scale and higher system level.

In this paper, we first review the available ML applications for ergonomics research in manufacturing (Section II), Then the research gaps, emerging opportunities, and potential challenges are discussed, from ML, ergonomics, and manufacturing perspectives (Section III). Finally, conclusions are formulated in Section IV.

This work is supported in part by NSF Grants No. 1928245 and 2026478.

Manuscript received: February 10, 2021; Revised May 12, 2021; Accepted May 25, 2021.

This paper was recommended for publication by Editor Editor Jingang Yi upon evaluation of the Associate Editor and Reviewers' comments.

[1] S. Lee, R. Radwin and J. Li are with the Department of Industrial and Systems Engineering, University of Wisconsin, Madison, WI 53706, USA. slee776@wisc.edu, rradwin@wisc.edu, jingshan.li@wisc.edu.

[2] L. Liu (Co-first author) is with School of Business Administration, Northeast University, Shenyang, Liaoning 210096, China. She is also with the Department of Industrial and Systems Engineering, University of Wisconsin-Madison, Madison, WI 53706, USA. liulineu@gmail.com.

Digital Object Identifier (DOI): see top of this page.

II. Literature Review

In this section, recent advances of using ML techniques for ergonomics research in manufacturing are reviewed, which is carried out by searching different combinations of keywords such as ML, AI, ergonomics, manufacturing, production, workload, fatigue, etc., in Google Scholar, Scopus, ScienceDirect, Web of Science, PubMed/Medline, and other databases in university libraries. Then the survey is structured in terms of models for individual operators, operator and workplace interactions, and system design and optimization.

A. Operator Model

Assessing, classifying, and evaluating the ergonomics risks of a human operator's activity in manufacturing are of significant importance. Both physical and mental workloads and fatigues need to be studied to identify the relationship between operator activities and work events, and quantify the association between human work posture and degree of ergonomics risk. Wearable devices, sensors, and videos are the main data sources to capture the operators' activities. Thus, an operator model for ergonomics risk can be studied from the perspectives of physical activity assessment (through sensor-based and video data) and risk stratification, mental workload evaluation, and fatigue classification.

1) Sensing-based Activity Assessment: Various sensors and wearable devices have been introduced to collect posture and kinematic data. A systematic review is presented in [4] to identify wearable devices proposed in the literature for ergonomic purposes and analyze how they can support the improvement of ergonomic conditions. Paper [5] uses body-mounted wearable sensors and ML techniques to monitor the risk of overexertion. Using kinematic data fed by wireless inertial measurement units (IMUs) and ML algorithms, a solution to recognize postural patterns is introduced in [6] to measure biomechanical risk in lifting load tasks. An efficient classification approach using random forest and support vector machine (SVM) models is developed in [7] to recognize static and dynamic work activities from a single accelerometer attached to the chest. Moreover, using the data collected from sensors on screwdrivers, paper [8] studies manual activity recognition by comparing datasets covering different tool movements, sensor placements with different classifiers, and observes that multiple sensors and ensemble deep learning methods can achieve superior performances.

2) Motion Analysis through Videos: In addition to sensing data, cameras and videos have been used extensively to capture human motion and gestures. Paper [9] develops a method to automatically compute the rapid upper limb assessment (RULA) scores through snapshots of digital videos via computer vision and ML techniques. Similarly, using convolutional neural network (CNN)-based pose detector to infer 2-D poses from images, and a deep neural network (DNN) to estimate RULA action levels, a real-time method is introduced in [10] to evaluate postural risk factors associated with MSDs. Paper [11] automatically quantifies repetitive hand activity with the use of digital video processing for the hand activity level (HAL). The technique is advanced in [12] and [13] using ML for time and motion studies in laboratory simulations of paced repetitive tasks for varying HAL and from videos of workers performing 50 industrial tasks based on decision tree and the proposed feature vector training algorithms. A graph-based multi-task learning approach is proposed in [14] for human postural assessment in long videos. In addition, a motion analysis system (MAS) utilizing a neural network model is developed in [15] to assess the ergonomic risk in manual and assembly activities through capturing operator movements and postures. Moreover, an application using Microsoft Kinect [16] is presented in paper [17] to employ ML algorithms, known as AdaBoost [18] Trigger indicator, to detect lifting and lowering gestures with real-time motion data capture on the shop floor for ergonomic evaluations and risk assessment.

Integrating sensing and video data with ergonomics models, paper [19] predicts real-time ergonomic risks for indoor operator movements and postures using spatiotemporal convolutional networks. Furthermore, statistical process control and data analytics techniques are used in [20] to develop a human motion analytics system to identify patterns of repetitive motions and the deviations from those patterns by collecting, transforming, storing, and analyzing data from repetitive physical motions performed by manufacturing workers.

3) Risk Stratification of Physical Workload: By creating and validating classifiers to distinguish between low and high risk manual lifting jobs contributed to low back disorders (LBD), paper [21] uses SVM, radial basis function neural network, and random forest models to predict the risk of LBDs. Similarly, SVM models are used in [22] to classify risks of occupational LBDs. A computer vision method is introduced in [23] to automatically classify lifting postures from simple features in video recordings using an elastic rectangular bounding box, drawn tightly around the subject, for classifying standing, stooping, and squatting at the lift origin and destination. The approach is further developed in [24] for an algorithm that automatically calculates a widely used risk prediction tool, the revised NIOSH (National Institute for Occupational Safety and Health) lifting equation using a single video camera. It is then extended in [25] for estimating the trunk flexion angle, angular speed, and angular acceleration by extracting simple features from the moving image during lifting. In addition, paper [26] demonstrates that computer vision and deep learning algorithms may be used for the automatic measurement of lifting load by analyzing body part movements extracted from a lifting video, without the need for stopping to weigh the object.

4) Mental Workload Evaluation: In addition to physical workload, mental workload and cognitive issues are also critical, and ML techniques can help for identification and evaluation. For example, neural network-based algorithms are proposed in [27]–[29] to assess mental workload, job satisfaction, and efficiency with respect to health, safety, environment, and ergonomics factors using survey data. Multimodal and ML methods are used in [30] to measure mental workload in simulated computer tasks and validate estimation indicators from physiological signals, subjective ratings of mental workload, and task performance. Using SVM and CNN algorithms, paper [31] analyzes and classifies mental workload states using Electroencephalogram (EEG) and functional Near-Infrared Spectroscopy (fNIRS) datasets.

5) Fatigue Classification: As an important element of ergonomics research, fatigue has been studied extensively. In recent years, ML methods have been utilized to classify fatigue states. For instance, a literature review of fatigue identification with application to human activity recognition using ML techniques is provided in [32].

Using Gaussian process regression to learn the complex relationship between individual human muscle forces, arm configuration, and arm endpoint force, paper [33] estimates individual muscle fatigue levels in human-robot co-manipulation scenarios, to optimize positions for task execution and alter endpoint force direction for maximal fatigue-related endurance time so that the fatigued muscle group can be relaxed and become active. An SVM approach is introduced in paper [34] to detect the changes in gait parameters measured by wearable sensors and classify the states into fatigued and non-fatigued ones following an occupational task. Moreover, a data analytic framework is introduced in [35] to manage fatigue in physically-demanding workplaces by using wearable sensor data to select feature and ML algorithms to capture different fatigue modes and phases. In [36], a neural network model is used for macro-postural classification to evaluate postural workload based on perceived discomforts and postural stress levels for various joint motions. Moreover, a recurrent neural network (RNN) model is presented in [37] to evaluate the fatigue factor caused by repetitive motions in manual material handling operations using 3D motion capture data.

B. Operator and Workspace Interaction Model

An operator's work always consists of interactions with the surroundings. Thus, the occupational safety concerns, impact of workplace environment, and in manufacturing, the collaboration between the human operator and the robots (or machines), are all related to the operator's risks.

1) Occupational Safety: Occupational health and safety (OHS) have a high priority in all workplaces. The OHS factors should integrate both qualitative and quantitative data dynamically and adaptively, drawn on expert elicitation and smart technologies, to reduce cumulative exposure of workers to OHS risks [38].

A Bayesian ML technique is applied in [39] to auto-code injury causation among 1.2 million state workers' compensation claims that may be preventable with biomechanical ergonomics or slip/trip/fall interventions to identify industry-specific ergonomics and safety prevention priorities. To classify ergonomics data, particularly for incomplete dataset, paper [40] uses feedforward neural networks with simulated annealing and conjugate gradient algorithms and forward selection of input variables to predict the risk of injuries in industrial jobs. A DNN model is described in [41] to study musculoskeletal injuries by detecting isometric grip exertions using facial videos and wearable photoplethysmograms.

In addition, paper [42] evaluates the performance of ML algorithms in classifying post-incident outcomes of occupational injuries based on injury factors extracted from 14,000 workers' compensation claims between 2008 and 2016 in the US Midwest region. To enhance safety in sensitive workplaces such as gas refineries, based on Bayesian and neural network models, paper [43] studies the effects of macro-ergonomics indicators on system safety efficiency by combining the expert's and operator's opinions to form the final criterion.

2) Workplace Environment: In addition to workplace safety, more aspects of working environment should also be considered. Neural network models with six input parameters (temperature, humidity, noise, luminosity, weight, and frequency) are introduced in [44] and [45] to quantify the ergonomics aspects of a workplace in manufacturing, characterized by three categories: good, medium, and poor. Also using a neural network model, paper [46] analyzes the effect of organizational safety climate and behavior on workplace injuries in Turkish metal casting industry based on surveys.

Through an adaptive network-based fuzzy inference system (ANFIS), survey data is used in [47] to assess staff productivity from motivational factors, health, safety, environmental, and ergonomics perspectives. From an ML-based human in the loop (HIP) simulation, the human choice complexity in a mixed model assembly line is studied in [48] to identify significant features affecting choice complexity and use them in a regression model to predict the impact of choice complexity on operator's effectiveness and overall throughput. Furthermore, paper [3] presents a conceptual framework that integrates several key concepts from the human factors engineering discipline that are important in the context of Industry 4.0, which should be considered in future workplace design.

3) Human-Robot Collaboration: As more robots are used in manufacturing, studies on collaborations between robots and humans are increasing. A systematic review of emerging research is presented in [49] to assess the state of the art for the design of safe and ergonomic collaborative robotic workcells. A publicly available human motion data set for collaborative robotics is provided in [50], which includes a series of six industry-oriented activities of postures and actions that are commonly observed in industrial settings and fully labeled according to the ergonomics assessment worksheet, such as screwing and manipulating loads under different conditions.

Using wearable sensors and inertial measurement units to capture the human upper body gestures, and an artificial neural network for static, dynamic, and composed gesture classification, paper [51] proposes a human robot interaction framework to study robot assistance to a human co-worker in delivering tools and parts, and holding objects to/for an assembly operation. Similarly, a unified human-robot collaboration framework is proposed in [52] to improve human ergonomics and the reconfigurability of production/assembly through real-time adaptation to human dynamic factors and intentions, which is composed of pose tracking, tool recognition, torque estimation, robot interaction and control, using DNN and a global finite state machine.

Furthermore, using a deep learning algorithm-based camera (https://aws.amazon.com/deeplens/) to recognize the operator, paper [53] introduces an approach to adapt a cobot workstation to operator skills to implement an efficient and safe synergy between robots and humans. In [54], deep learning-based human motion recognition techniques, enabled by a deep CNN structure adapted from AlexNet [55], are developed to predict the needs for human-robot collaboration, leading to improved robot planning and control in accomplishing a shared task.

C. System Design and Optimization Model

In a manufacturing system, all operators' activities are interconnected and their impacts can propagate throughout the system. Thus, ergonomics measures should be considered in all aspects of manufacturing system design and optimization, from products to tasks and processes.

1) Product Design: Using ML technology, more ergonomics issues can be considered in product development. For example, through an empirical study, paper [56] proposes a neural network-based data mining framework to generate useful patterns for developing standard size charts for apparel. Using a neural network to classify proper and defective signals in connector assembly lines, a digital assembly glove with wearable sensors is described in [57] to measure vibration and force values on fingers to detect defective processes. Also, a wearable solution is presented in [58], which uses signals from a trunk IMU and pressure insoles with a gradient boosted decision tree algorithm to provide a practical, automated, and accurate monitoring of time series lumbar moments across a broad range of material handling tasks.

2) Task Assignment: As cycle times play a key role in planning and scheduling, using skeleton and depth data of a Kinect sensor, paper [59] introduces three classification trees and their fusions and applies discriminant analysis to estimate cycle times in computer assembly. To evaluate task performance, a data-driven approach is introduced in [60] for repetitive precision tasks, using kinematics, electromyography, and heart rate data collected from wearable sensors, with a linear discriminant analysis algorithm, where the kinematic data provides the most promising classification performance. In addition, a mutualistic and adaptive human-machine collaboration framework is proposed in [61] to continuously monitor worker's physiological parameters, measured by wearable devices, and couple them with process information to dynamically assign tasks to either humans or cobots in an injection molding manufacturing line, where a random forest algorithm is used to classify workers' fatigue levels.

3) Process Planning: In addition to product design and task assignment, ML methods can be applied for process planning and system design. For example, by combining neural network and RULA analysis, paper [62] introduces an experimental study of ergonomic workstations redesign process for automotive assembly lines. Using verbal parameters of profile of mood states and non-verbal parameters of heart rate in a given workplace environment, a neural network model is presented in [63] to evaluate work performance in a medium-scale food production system.

Moreover, extending from traditional manufacturing to business processes such as supply chain, paper [64] reviews the current ergonomics design approaches in delivering digital solutions, and proposes an interaction, process, integration and intelligence (IPII) design approach, by leveraging ML technologies for future ergonomics practices. Through integrating IoT (internet of things) paradigm and AI techniques in cold chain risk management, paper [65] introduces a real-time monitoring system for quality control and cold-associated occupational safety risk assessment by considering the surrounding environment and the operators' personal health status.

III. Research Opportunities and Challenges

The available results have proved that extensive success and significant impact can be achieved by using ML technology for ergonomics research in manufacturing. Various ML methods, such as neural network, random forest, AdaBoost, multivariate linear regression, deep learning, SVM, reinforce learning, have been utilized, based on the data from sensors, cameras, experiments, records and surveys, etc., to solve a broad range of ergonomics problems in manufacturing, from risk analysis (e.g., physical and mental workloads) and classification for operators and workplace, to design and optimization issues (such as planning and assignment). Such developments suggest that ML in manufacturing ergonomics is an area with explosive and promising opportunities. However, there still exist significant research gaps and challenges to achieve high fidelity, operator-specific, dynamic, and systematic analysis of ergonomics risks, using which prompt and optimal actions are expected to be taken to improve the overall safety, productivity, and sustainability performance in manufacturing. To promote and incentivize future research in this area, potential opportunities and challenges are summarized below, from the perspectives of ML methodology, ergonomics consideration, and manufacturing systems.

A. Machine Learning Perspective

ML is a data-driven methodology relying on big data, which, however, may not be accessible in practice. It is not uncommon that only limited data collection or small and incomplete dataset is available. Moreover, many ML methods may not be able to capture causal inferences and dynamic nature in datasets. Such limitations propose more challenges for ML applications in manufacturing ergonomics research.

1) Data Availability: The application of ML technology requires a substantial amount of data for training, learning, and predicting. For ergonomics study in manufacturing using ML, the data can come from different sources, including videos or images from cameras, movement or biomedical data from multiple sensors, as well as data from experiments, simulations, and surveys or questionnaires. In addition, claims, notes, or reports may also be additional sources. However, sometimes the data may not be easy to access due to policy, environment, privacy, and behavior concerns in manufacturing. Furthermore, data collection can be difficult depending on the technology behind data sources. Specifically, motion capture systems or data from cameras and multiple sensors may require considerable costs of devices and experiments.

The availability of data and difficulties in data collection could be obstacles to conducting ML research in manufacturing ergonomics. These complications can be alleviated by sharing collected data or sources for different studies or combining various types of existing data. When sharing data or model is considered, transfer learning [66] can be one of the options that can be utilized to improve resulting models, but it should be compatible with the data sources. When combining different data is adopted, such data may have mixed formats or dimensions, such as quantitative or qualitative, discrete or continuous, numerical or descriptive, which may introduce substantial difficulty to mine, convert or explain. The ML technology needs to combine different types of data for complex analysis. All these will present significant challenges to existing ML methodologies and demand the development of novel and effective methods.

2) Small and Incomplete Dataset: To apply ML methods, not only data availability can be an issue, but also the dataset itself. For many ML methods, such as neural network, SVM, random forest, and deep learning, they are more effective to deal with large datasets. However, in manufacturing ergonomics, small and imbalanced datasets with missing or incoomlete data are typical, and usually have large variations. Especially, when human subjects are involved in data collection including motion captures, more efforts and time are required, and the size of dataset is limited to the number of participants in the experiments or surveys. Moreover, when claims, surveys, or reports are utilized, data quality often becomes an issue as there usually exist missing data, incorrect and incomplete records. These add additional difficulty to data utilization. Developing innovative ML methods to solve such issues is of significant importance.

3) Causal Relationship: Many machine learning methods seek to discover correlations between variables and outcomes. Although associations are important, they may not represent the causal relationships. As many ergonomics issues, particularly those related to cognitive and mental workload, may be subjective or lack clear inferences of fundamental knowledge, the correlations may not be enough to derive policies or decisions for subsequent control and implementations. Therefore, there is a great need to develop causal models so that the effect of variable manipulations can be inferred, which can be used to design optimal actions. Although causal models have been introduced in ML research (e.g., monographs [67], [68]), the application is still limited. More developments of appropriate causal models to strengthen manufacturing ergonomics study in both theory and practice are necessary.

4) Time Sensitivity: Many current studies consider static behavior in the system. In manufacturing ergonomics study, not only is static or average performance important, but also the transient behavior needs to be addressed. For instance, the fatigue level or mental workload may change over time. Risks of certain injuries may be triggered or elevated randomly. All these require computational efficient algorithms to quickly identify and quantify the risks and respond appropriately to eliminate them in real time. Thus, control or optimization methods based on ML algorithms should be able to take immediate actions in those time-sensitive issues. Reinforcement learning [69] or models based on Markov decision processes [70] can be optional models to deal with such issues. In addition, when motion capture systems are set up or sensors are installed in manufacturing facilities, data can keep collected continuously. Then, the models should be updated in real-time to improve the results by utilizing additional data. Appropriate learning paradigms such as evolutionary algorithms [71] could be considered to deal with these challenges.

B. Ergonomics Perspective

To respond to the upcoming challenges of Industry 4.0 characterized by new technologies of robotics, AI, biotechnology, and quantum computing, ergonomics methods and practice need to be changed, adapted, supplemented, and augmented using a "radical systems thinking" approach [72]. ML techniques should be more accessible, understood, and accepted in the ergonomics community in order to help ergonomics researchers greatly with realized benefits [73]. However, the existing ML applications in ergonomics research are typically isolated and narrowly subjected, without becoming an integral component in manufacturing. Therefore, in addition to the topics summarized in Section II, the following directions and areas could have promising research opportunities, covering from individual operator models, to interactions with workplace, and decision support for manufacturing systems.

1) Integrated Worker-Specific Risk Analysis: In the past decades, both physical and mental workloads have been studied extensively in ergonomics research [2], [74]. Since either workload can affect the other one, both workloads should be modeled, analyzed, and evaluated simultaneously, and the relationship between them needs to be identified. Future studies should focus on integrating the physical and mental workloads and their correlations, which can lead to improvement in occupational safety and health. In addition, using ML models for individualized analysis targeting to each operator's specific features is an interesting direction. Such work will become more important and complicated when aging workforce is considered.

In addition to data analytics methods, biomechanics laws based on physics principles have been prevailing approaches to evaluate operators risks in manufacturing. Ergonomics evaluation of work can be conducted using biomechanical models to analyze single movements or body postures, and taking internal forces in muscles and joints into account. However, such models can be limited due to lack of applicable conditions. ML techniques can compensate such constraints. Thus, integrating biomechnics laws with ML methods could benefit from both advantages. For instance, the data-driven approach with biomechanical parameters input has proved that it can be used to predict the occurrence and level of physical fatigue [75]. Again, the model could be adapted for personalized study based on each operator's characteristics. Thus, more ML approaches that use biomechanical data and operator's profile need to be developed to predict the ergonomics risk in manufacturing systems.

2) Human-Machine Interaction: Both human operators and robots or machines are essential parts of manufacturing systems with significant advantages in production processes. The extensive use of robots through human-robot cooperation could realize the advantages, but may also impact workload, both physically and mentally. There is no doubt that with the advent of Industry 4.0, more robots will be involved in manufacturing. Numerous studies have shown that human workload can be decreased due to the involvement of robots [76], [77]. However, there is also evidence that increased levels of robot autonomy would lead to higher mental workload [78]. Therefore, more manufacturing principles and propositions need to be provided to decrease operator workload in human-robot interaction settings. As described in [79], developing technical, human-related, and normative requirements and standards for human-robot/machine interaction to ensure occupational safety in ergonomic workspace and assembly process is important. Moreover, consideration of different cognitive features of each operator will be desirable. ML techniques can be key enablers in developing such principles.

3) Optimal Decision Support: As more intelligent equipment and devices are installed on the factory floor, there is a need to better use them in decision support to help reduce workloads and improve safety while increasing manufacturing productivity. As many risks, such as fatigue and mental workloads, are increasing with time and may only become evident after a certain time period, it is also not easy to check and verify the results before its happening, particularly when operators have a diverse background and skill set. Therefore, early detection of these risks and derivation of real-time and optimal decisions to avoid potential injuries and production losses become critical, especially when operators' profiles are considered. Paper [80] reviews the strategic use of AI, mainly ML, from the perspectives of supporting decision making process, improving customer relationship and employees engagement, and enabling machine-to-machine communication in new products and services. Therefore, applying ML techniques to identify patterns and risk signals, predict outcomes, and then provide optimal and specific action decisions will be an important direction in the future.

To increase productivity, ML methods can help assess staff performance from motivational factors, health, safety, environmental, and ergonomics perspectives. Developing optimization frameworks (e.g., [81], [82]) to integrate intelligent equipment with physical strains of workers and productivity performance in manufacturing processes is needed. Such frameworks need to be adaptable to different manufacturing scenarios, by identifying process features, classifying operators' and equipment activities, evaluating safety concerns, and then adjusting their collaborations to accommodate these features, activities, and concerns, where ML techniques can play a significant role. Moreover, from a plant architecture perspective, it is argued in [83] that in the new era of information technology and deep learning, industrial architectures can help fit technology to humans to assure wellbeing and health with ergonomics optimization of all design aspects.

C. Manufacturing Systems Perspective

The existing research in manufacturing system design, scheduling, and control is typically carried out separately, with only limited attention on ergonomics issues. However, a manufacturing system includes machines, people, and products, and all are associated with human behavior and ergonomics risks, which should be systematically and integrally studied. In other words, human-centered management equipped with Industry 4.0 is the key to support smart and sustainable manufacturing [84]. Given the opportunities and challenges described above from ML and ergonomics perspectives, integrating them into manufacturing systems will generate fruitful results, which will be discussed from system design, scheduling and control, and enterprise planning perspectives next.

1) Integration with Product and Manufacturing System Design: In product development, not only the manufacturability and customer experiences should be considered, but also be the ergonomics risks, as some product features are correlated with the risk during manufacturing. For example, repetitive wiring tasks on assembly lines may increase the risk of MSD at hand, wrist, and arm. Such features are also coupled with manufacturing system design, where capacity planning (such as cycle time distribution), product allocation (set up frequency and lot size) and layout selection (e.g., serial, work cell or U-shaped lines), etc., may also impact the risk. However, such issues have not been considered in an integrated manner. Therefore, developing models to study the trade-offs to balance multiple objectives from different perspectives is needed. Applying ML technology in design phase to identify and evaluate potential risks, and utilizing the results to seek optimal solutions need to be explored.

2) Integration with Production Scheduling and Control: The existing ergonomics research on task assignment and scheduling only list ergonomics risk as a constraint without considering their interactions. However, task assignment and scheduling are tightly coupled with physical and mental workloads. For instance, task cycle time can impact fatigue and mental workload, leading to work-related disorders, which in turn may introduce more variations in cycle time, resulting in reduced throughput. In addition, the operator's characteristics play an important role to carry out the tasks, which should be included in the analysis. Using ML methods can help better classify task features, identify operator profile, and predict states of potential risks. Integrating these into an optimization model can make production planning and scheduling more efficient and effective.

Many production control work focuses on machine operations only without considering the impact on operator's behavior. However, control actions on machines and ergonomics risks on operators could have strong interactions. For example, frequent adjustment of machine status may induce pressures on operators and increase their ergonomic risks, which can propagate to up- and downstream stations, finally causing more variations and losses in production. Such pressures may also result in low product quality reducing effective system throughput. Such outcomes can intrigue more adjustments and pressures, leading to further losses. Moreover, such impacts could be machine and operator specific with large variations among different workers. Applying techniques to identify operator characteristics with respect to various actions and outcomes and investigate the impacts in a closed loop can better address their correlations, and help design optimal and personalized control policies.

3) Integration with a Broader Manufacturing Community: A manufacturing enterprise includes not only production shops, but also warehouses, supply chains, as well as business processes and customer service, etc. When a broader manufacturing community is considered, more entities with different or even conflict goals and diverse human groups exist in the enterprise. The ergonomics risks and business objectives are not only complex, but also coupled with each. In addition, the safety and environmental issues and workers' preferences should be embedded in the workplace model. Moreover, the personnel, team and organization managements become more critical, and can impact workers' activities and rational behaviors as well as the ergonomics risks, which will feedback to influence business outcomes. Such issues will be more complicated when labor cost, aging, or ethics considerations are taken into account. It is expected that ML techniques with integrated system engineering approaches can help address the ergonomics and related issues in a broader manufacturing area and contribute to the benefits of whole enterprise and overall manufacturing industry or society.

IV. CONCLUSIONS

The rapid development of machine learning and information technology has brought in substantial opportunities and innovations to ergonomics and manufacturing. With ML technology, manufacturing ergonomics research is advancing from population-based, static, and siloed analyses towards individualized, real-time, and integrated studies. Developing novel ML methodologies to address new ergonomics and manufacturing challenges will lead to promising and meaningful studies in a new paradigm. Promoting such a research program requires collaborative efforts from researchers in multiple disciplines, such as human factors, operations research, manufacturing, computer science, psychology, and others, using integrated and complemented tools and methodologies, in both hardware and software (such as devices and algorithms), to solve complex and significant issues.

REFERENCES

[1] Bureau of Labor Statistics, "Fact sheet: Occupational injuries and illnesses resulting in musculoskeletal disorders (MSDs)," *https://www.bls.gov/iif/oshwc/case/msds.htm*, 2020.

[2] B. A. Kadir, O. Broberg, and C. S. da Conceição, "Current research and future perspectives on human factors and ergonomics in industry 4.0," *Computers & Industrial Engineering*, vol. 137, p. 106004, 2019.

[3] W. P. Neumann, S. Winkelhaus, E. H. Grosse, and C. H. Glock, "Industry 4.0 and the human factor – a systems framework and analysis methodology for successful development," *International Journal of Production Economics*, vol. 233, p. 107992, 2021.

[4] E. Stefana, F. Marciano, D. Rossi, P. Cocca, and G. Tomasoni, "Wearable devices for ergonomics: A systematic literature review," *Sensors*, vol. 21, no. 3, 2021.

[5] N. D. Nath, T. Chaspari, and A. H. Behzadan, "Automated ergonomic risk monitoring using body-mounted sensors and machine learning," *Advanced Engineering Informatics*, vol. 38, pp. 514–526, 2018.

[6] I. Conforti, I. Mileti, Z. Del Prete, and E. Palermo, "Measuring biomechanical risk in lifting load tasks through wearable system and machine-learning approach," *Sensors*, vol. 20, no. 6, p. 1557, 2020.

[7] S. M. Hosseinian, Y. Zhu, R. K. Mehta, M. Erraguntla, and M. A. Lawley, "Static and dynamic work activity classification from a single accelerometer: implications for ergonomic assessment of manual handling tasks," *IISE Transactions on Occupational Ergonomics and Human Factors*, vol. 7, no. 1, pp. 59–68, 2019.

[8] L. C. Günther, S. Kärcher, and T. Bauernhansl, "Activity recognition in manual manufacturing: detecting screwing processes from sensor data," *Procedia CIRP*, vol. 81, pp. 1177–1182, 2019.

[9] M. MassirisFernández, J. Á. Fernández, J. M. Bajo, and C. A. Delrieux, "Ergonomic risk assessment based on computer vision and machine learning," *Computers & Industrial Engineering*, vol. 149, p. 106816, 2020.

[10] L. Li, T. Martin, and X. Xu, "A novel vision-based real-time method for evaluating postural risk factors associated with musculoskeletal disorders," *Applied Ergonomics*, vol. 87, p. 103138, 2020.

[11] C.-H. Chen, Y. H. Hu, T. Y. Yen, and R. G. Radwin, "Automated video exposure assessment of repetitive hand activity level for a load transfer task," *Human Factors*, vol. 55, no. 2, pp. 298–308, 2013.

[12] O. Akkas, C.-H. Lee, Y. H. Hu, T. Y. Yen, and R. G. Radwin, "Measuring elemental time and duty cycle using automated video processing," *Ergonomics*, vol. 59, no. 11, pp. 1514–1525, 2016.

[13] O. Akkas, C. H. Lee, Y. H. Hu, C. Harris Adamson, D. Rempel, and R. G. Radwin, "Measuring exertion time, duty cycle and hand activity level for industrial tasks using computer vision," *Ergonomics*, vol. 60, no. 12, pp. 1730–1738, 2017.

[14] B. Parsa and A. G. Banerjee, "A multi-task learning approach for human action detection and ergonomics risk assessment," *arXiv preprint arXiv:2008.03014*, 2020.

[15] M. Bortolini, M. Gamberi, F. Pilati, and A. Regattieri, "Automatic assessment of the ergonomic risk for manual manufacturing and assembly activities through optical motion capture technology," *Procedia CIRP*, vol. 72, pp. 81–86, 2018.

[16] Z. Zhang, "Microsoft kinect sensor and its effect," *IEEE Multimedia*, vol. 19, no. 2, pp. 4–10, 2012.

[17] C. E. Mgbemena, J. Oyekan, A. Tiwari, Y. Xu, S. Fletcher, W. Hutabarat, and V. Prabhu, "Gesture detection towards real-time ergonomic analysis for intelligent automation assistance," in *Advances in Ergonomics of Manufacturing: Managing the Enterprise of the Future*, pp. 217–228, Springer, 2016.

[18] Y. Freund and R. E. Schapire, "A decision-theoretic generalization of on-line learning and an application to boosting," *Journal of Computer and System Sciences*, vol. 55, no. 1, pp. 119–139, 1997.

[19] B. Parsa, E. U. Samani, R. Hendrix, S. M. Singh, S. Devasia, and A. G. Banerjee, "Predicting ergonomic risks during indoor object manipulation using spatiotemporal convolutional networks," *CoRR*, 2019.

[20] D. C. Wierschem, J. A. Jimenez, and F. A. M. Mediavilla, "A motion capture system for the study of human manufacturing repetitive motions," *The International Journal of Advanced Manufacturing Technology*, vol. 110, no. 3, pp. 813–827, 2020.

[21] J. Zurada, "Predicting the risk of low back disorders due to manual handling tasks," in *Hawaii International Conference on System Sciences*, pp. 1080–1088, 2012.

[22] M. Erdem, F. E. Boran, and D. Akay, "Classification of risks of occupational low back disorders with support vector machines," *Human Factors and Ergonomics in Manufacturing & Service Industries*, vol. 26, no. 5, pp. 550–558, 2016.

[23] R. L. Greene, Y. H. Hu, N. Difranco, X. Wang, M.-L. Lu, S. Bao, J.-H. Lin, and R. G. Radwin, "Predicting sagittal plane lifting postures from image bounding box dimensions," *Human Factors*, vol. 61, no. 1, pp. 64–77, 2019.

[24] X. Wang, Y. H. Hu, M.-L. Lu, and R. G. Radwin, "The accuracy of a 2d video-based lifting monitor," *Ergonomics*, vol. 62, no. 8, pp. 1043–1054, 2019.

[25] R. L. Greene, M.-L. Lu, M. S. Barim, X. Wang, M. Hayden, Y. H. Hu, and R. G. Radwin, "Estimating trunk angle kinematics during lifting using a computationally efficient computer vision method," *Human Factors*, p. 0018720820958840, 2020.

[26] Y. Li, R. L. Greene, M. Fangzhou, Y. H. Hu, and R. G. Radwin, "Towards video-based automatic lifting load prediction," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 2020.

[27] A. Azadeh, M. Rouzbahman, M. Saberi, and I. M. Fam, "An adaptive neural network algorithm for assessment and improvement of job satisfaction with respect to HSE and ergonomics program: the case of a gas refinery," *Journal of Loss Prevention in the Process Industries*, vol. 24, no. 4, pp. 361–370, 2011.

[28] A. Azadeh, M. Rouzbahman, M. Saberi, F. Valianpour, and A. Keramati, "Improved prediction of mental workload versus HSE and ergonomics factors by an adaptive intelligent algorithm," *Safety Science*, vol. 58, pp. 59–75, 2013.

[29] A. Azadeh, M. Saberi, M. Rouzbahman, and F. Valianpour, "A neuro-fuzzy algorithm for assessment of health, safety, environment and ergonomics in a large petrochemical plant," *Journal of Loss Prevention in the Process Industries*, vol. 34, pp. 100–114, 2015.

[30] Y. Ding, Y. Cao, V. G. Duffy, Y. Wang, and X. Zhang, "Measurement and identification of mental workload during simulated computer tasks with multimodal methods and machine learning," *Ergonomics*, pp. 1–13, 2020.

[31] U. Asgher, K. Khalil, Y. Ayaz, R. Ahmad, and M. J. Khan, "Classification of mental workload (MWL) using support vector machines (SVM) and convolutional neural networks (CNN)," in *The 3rd International Conference on Computing, Mathematics and Engineering Technologies*, pp. 1–6, 2020.

[32] K. Gonzalez, F. Sasangohar, R. K. Mehta, M. Lawley, and M. Erraguntla, "Measuring fatigue through heart rate variability and activity recognition: a scoping literature review of machine learning techniques," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 61, pp. 1748–1752, 2017.

[33] L. Peternel, C. Fang, N. Tsagarakis, and A. Ajoudani, "A selective muscle fatigue management approach to ergonomic human-robot co-manipulation," *Robotics and Computer-Integrated Manufacturing*, vol. 58, pp. 69–79, 2019.

[34] A. Baghdadi, F. M. Megahed, E. T. Esfahani, and L. A. Cavuoto, "A machine learning approach to detect changes in gait parameters following a fatiguing occupational task," *Ergonomics*, vol. 61, no. 8, pp. 1116–1129, 2018.

[35] Z. S. Maman, Y.-J. Chen, A. Baghdadi, S. Lombardo, L. A. Cavuoto, and F. M. Megahed, "A data analytic framework for physical fatigue management using wearable sensors," *Expert Systems with Applications*, p. 113405, 2020.

[36] M. K. Chung, I. Lee, D. Kee, and S. H. Kim, "A postural workload evaluation system based on a macro-postural classification," *Human Factors and Ergonomics in Manufacturing & Service Industries*, vol. 12, no. 3, pp. 267–277, 2002.

[37] G. Hernandez, D. Valles, D. C. Wierschem, R. M. Koldenhoven, G. Koutitas, F. A. Mendez, S. Aslan, and J. Jimenez, "Machine learning techniques for motion analysis of fatigue from manual material handling operations using 3D motion capture data," in *Annual Computing and Communication Workshop and Conference*, pp. 300–305, 2020.

[38] L. Drankoff, "A systems engineering framework for integration of cognitive ergonomics in smart factory configurations," *Journal of Management & Engineering Integration*, vol. 13, no. 1, pp. 53–62, 2020.

[39] A. R. Meyers, I. S. Al-Tarawneh, S. J. Wurzelbacher, P. T. Bushnell, M. M. P. Lampl, J. L. Bell, S. J. Bertke, M. D. C. Robins, C.-Y. Tseng, C. Wei, *et al.*, "Applying machine learning to workers' compensation data to identify industry-specific ergonomic and safety prevention priorities: Ohio, 2001 to 2011," *Journal of Occupational and Environmental Medicine*, vol. 60, no. 1, p. 55, 2018.

[40] C.-L. Chen, D. B. Kaber, and P. G. Dempsey, "Using feedforward neural networks and forward selection of input variables for an ergonomics data classification problem," *Human Factors and Ergonomics in Manufacturing & Service Industries*, vol. 14, no. 1, pp. 31–49, 2004.

[41] H. Asadi, G. Zhou, J. J. Lee, V. Aggarwal, and D. Yu, "A computer vision approach for classifying isometric grip force exertion levels," *Ergonomics*, vol. 63, no. 8, pp. 1010–1026, 2020.

[42] F. D. Kakhki, S. A. Freeman, and G. A. Mosher, "Utilization of machine learning in analyzing post-incident state of occupational injuries in

Agro-manufacturing industries," in *International Conference on Applied Human Factors and Ergonomics*, pp. 3–9, 2020.

[43] A. Taghi-Molla, M. Rabbani, M. H. K. Gavareshki, and E. Dehghani, "Safety improvement in a gas refinery based on resilience engineering and macro-ergonomics indicators: a bayesian network–artificial neural network approach," *International Journal of System Assurance Engineering and Management*, pp. 1–14, 2020.

[44] A. Ene and D.-C. Anghel, "A neural networks application in ergonomics," in *Proceedings of the International Conference on Electronics, Computers and Artificial Intelligence*, pp. 1–4, 2013.

[45] D. C. Anghel and N. Belu, "Contributions to ranking an ergonomic workstation, considering the human effort and the microclimate parameters, using neural networks," in *Applied Mechanics and Materials*, vol. 371, pp. 812–816, Trans Tech Publ, 2013.

[46] A. M. Abubakar, H. Karadal, S. W. Bayighomog, and E. Merdan, "Workplace injuries, safety climate and behaviors: application of an artificial neural network," *International Journal of Occupational Safety and Ergonomics*, pp. 1–11, 2018.

[47] A. Azadeh and M. Zarrin, "An intelligent framework for productivity assessment and analysis of human resource from resilience engineering, motivational factors, hse and ergonomics perspectives," *Safety Science*, vol. 89, pp. 55–71, 2016.

[48] M. Busogi and N. Kim, "Analytical modeling of human choice complexity in a mixed model assembly line using machine learning-based human in the loop simulation," *IEEE Access*, vol. 5, pp. 10434–10444, 2017.

[49] L. Gualtieri, E. Rauch, and R. Vidoni, "Emerging research fields in safety and ergonomics in industrial collaborative robotics: a systematic literature review," *Robotics and Computer-Integrated Manufacturing*, vol. 67, p. 101998, 2020.

[50] P. Maurice, A. Malaisé, C. Amiot, N. Paris, G.-J. Richard, O. Rochel, and S. Ivaldi, "Human movement and ergonomics: an industry-oriented dataset for collaborative robotics," *The International Journal of Robotics Research*, vol. 38, no. 14, pp. 1529–1537, 2019.

[51] P. Neto, M. Simão, N. Mendes, and M. Safeea, "Gesture-based human-robot interaction for human assistance in manufacturing," *The International Journal of Advanced Manufacturing Technology*, vol. 101, no. 1-4, pp. 119–135, 2019.

[52] W. Kim, M. Lorenzini, P. Balatti, P. Nguyen, U. Pattacini, V. Tikhanoff, L. Peternel, C. Fantacci, L. Natale, G. Metta, *et al.*, "A reconfigurable and adaptive human-robot collaboration framework for improving worker ergonomics and productivity," *IEEE Robotics and Automation Magazine*, 2019.

[53] O. D. M. Lázaro, W. M. Mohammed, B. R. Ferrer, R. Bejarano, and J. L. M. Lastra, "An approach for adapting a cobot workstation to human operator within a deep learning camera," in *IEEE International Conference on Industrial Informatics*, vol. 1, pp. 789–794, 2019.

[54] P. Wang, H. Liu, L. Wang, and R. X. Gao, "Deep learning-based human motion recognition for predictive context-aware human-robot collaboration," *CIRP Annals*, vol. 67, no. 1, pp. 17–20, 2018.

[55] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," *Advances in Neural Information Processing Systems*, vol. 25, pp. 1097–1105, 2012.

[56] C.-Y. Tsai and C.-H. Hsu, "Developing standard elderly aged female size charts based on anthropometric data to improve manufacturing using artificial neural network-based data mining," *Theoretical Issues in Ergonomics Science*, vol. 14, no. 3, pp. 258–272, 2013.

[57] I. Kucukoglu, H. Atici-Ulusu, T. Gunduz, and O. Tokcalar, "Application of the artificial neural network method to detect defective assembling processes by using a wearable technology," *Journal of Manufacturing Systems*, vol. 49, pp. 163–171, 2018.

[58] E. S. Matijevich, P. Volgyesi, and K. E. Zelik, "A promising wearable solution for the practical and accurate monitoring of low back loading in manual material handling," *Sensors*, vol. 21, no. 2, p. 340, 2021.

[59] Á. Lipovits, M. Gál, P. J. Kiss, and C. Süveges, "Human motion detection in manufacturing process," in *World Congress on Electrical Engineering and Computer Systems and Science*, pp. 111–118, 2016.

[60] L. Tsao, M. A. Nussbaum, S. Kim, and L. Ma, "Modelling performance during repetitive precision tasks using wearable sensors: a data-driven approach," *Ergonomics*, pp. 1–19, 2020.

[61] A. Bettoni, E. Montini, M. Righi, V. Villani, R. Tsvetanov, S. Borgia, C. Secchi, and E. Carpanzano, "Mutualistic and adaptive human-machine collaboration based on machine learning in an injection moulding manufacturing line," *Procedia CIRP*, vol. 93, pp. 395–400, 2020.

[62] D.-C. Anghel, E.-L. Niţu, A.-D. Rizea, A. Gavriluţă, A. Gavriluţă, and N. Belu, "Ergonomics study on an assembly line used in the automotive industry," in *MATEC Web of Conferences*, vol. 290, p. 12001, 2019.

[63] M. Ushada, T. Okayama, A. Suyantohadi, N. Khuriyati, and H. Murase, "Kansei engineering-based artificial neural network model to evaluate worker performance in small-medium scale food production system," *International Journal of Industrial and Systems Engineering*, vol. 27, no. 1, pp. 28–47, 2017.

[64] W. Xu, D. Furie, M. Mahabhaleshwar, B. Suresh, and H. Chouhan, "Applications of an interaction, process, integration and intelligence (IPII) design approach for ergonomics solutions," *Ergonomics*, vol. 62, no. 7, pp. 954–980, 2019.

[65] Y. P. Tsang, K. L. Choy, C.-H. Wu, G. T. Ho, C. H. Lam, and P. Koo, "An internet of things (IoT)-based risk monitoring system for managing cold supply chain risks," *Industrial Management & Data Systems*, 2018.

[66] S. J. Pan and Q. Yang, "A survey on transfer learning," *IEEE Transactions on Knowledge and Data Engineering*, vol. 22, no. 10, pp. 1345–1359, 2009.

[67] J. Pearl, *Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference*. Morgan Kaufmann Publishers, 1997.

[68] J. Pearl, *Causality: Models, Reasoning, and Inference*. Cambridge University Press, 2000.

[69] R. S. Sutton and A. G. Barto, *Reinforcement Learning: An Introduction*. MIT press, 2018.

[70] M. L. Puterman, *Markov Decision Processes: Discrete Stochastic Dynamic Programming*. John Wiley & Sons, 2014.

[71] P. A. Vikhar, "Evolutionary algorithms: a critical review and its future prospects," in *International Conference on Global Trends in Signal Processing, Information Computing and Communication*, pp. 261–265, 2016.

[72] M. Holman, G. Walker, T. Lansdown, and A. Hulme, "Radical systems thinking and the future role of computational modelling in ergonomics: an exploration of agent-based modelling," *Ergonomics*, vol. 63, no. 8, pp. 1057–1074, 2020.

[73] G. J. Read, P. M. Salmon, J. Thompson, and R. J. McClure, "Simulating the behaviour of complex systems: cmputational modelling in ergonomics," *Ergonomics*, vol. 63, no. 8, pp. 931–937, 2020.

[74] X. Sun, R. Houssin, J. Renaud, and M. Gardoni, "A review of methodologies for integrating human factors and ergonomics in engineering design," *International Journal of Production Research*, vol. 57, no. 15-16, pp. 4961–4976, 2019.

[75] Z. S. Maman, M. A. A. Yazdi, L. A. Cavuoto, and F. M. Megahed, "A data-driven approach to modeling physical fatigue in the workplace using wearable sensors," *Applied Ergonomics*, vol. 65, pp. 515–529, 2017.

[76] C. T. Landi, V. Villani, F. Ferraguti, L. Sabattini, C. Secchi, and C. Fantuzzi, "Relieving operators' workload: towards affective robotics in industrial scenarios," *Mechatronics*, vol. 54, pp. 144–154, 2018.

[77] M. Lohse, R. Rothuis, J. Gallego-Pérez, D. E. Karreman, and V. Evers, "Robot gestures make difficult tasks easier: the impact of gestures on perceived workload and task performance," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pp. 1459–1466, 2014.

[78] M. Kaufeld and P. Nickel, "Level of robot autonomy and information aids in human-robot interaction affect human mental workload–an investigation in virtual reality," in *International Conference on Human-Computer Interaction*, pp. 278–291, 2019.

[79] M. Faber, J. Bützler, and C. M. Schlick, "Human-robot cooperation in future production systems: analysis of requirements for designing an ergonomic work system," *Procedia Manufacturing*, vol. 3, pp. 510–517, 2015.

[80] A. F. Borges, F. J. Laurindo, M. M. Spínola, R. F. Gonçalves, and C. A. Mattos, "The strategic use of artificial intelligence in the digital era: Systematic literature review and future research directions," *International Journal of Information Management*, vol. 57, p. 102225, 2021.

[81] M. Pearce, B. Mutlu, J. Shah, and R. Radwin, "Optimizing makespan and ergonomics in integrating collaborative robots into manufacturing processes," *IEEE Transactions on Automation Science and Engineering*, vol. 15, no. 4, pp. 1772–1784, 2018.

[82] Y.-J. Zhang, L. Liu, N. Huang, R. Radwin, and J. Li, "From manual operation to collaborative robot assembly: an integrated model of productivity and ergonomic performance," *IEEE Robotics and Automation Letters*, vol. 6, no. 2, pp. 895–902, 2021.

[83] P. Horn, "New challenges for the industrial architecture: ergonomics on the edge of a new era of IT technology and deep learning," in *International Conference on Applied Human Factors and Ergonomics*, pp. 400–407, 2018.

[84] F. Sgarbossa, E. H. Grosse, W. P. Neumann, D. Battini, and C. H. Glock, "Human factors in production and logistics systems of the future," *Annual Reviews in Control*, 2020.