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THE EYES OF TOMORROW: HOW AI-POWERED COMPUTER VISION WILL REVOLUTIONIZE MANUFACTURING AND ROBOTICS

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Abstract

This paper explores the ways in which industrial labor, production efficiency, and socio-technical systems are reinvented by AI-powered computer vision. Computer vision is changing the field of manufacturing and robotics through artificial intelligence (AI) and allowing a degree of automation, precision, and flexibility never seen before. In spite of the large-scale technological development, social and organizational consequences of these innovations are under-researched. We position our research at the crossroads of the technological innovation and social science investigation, based on the recent research in the field of the AI application (Krizhevsky, Sutskever, and Hinton, 2017; LeCun, Bengio, and Hinton, 2015). With a qualitative synthesis of secondary sources, such as benchmark studies on convolutional neural networks (CNNs), reinforcement learning frameworks and robotics applications in the industry (Patel et al., 2019; Goodfellow, Bengio, and Courville, 2016), we evaluate the disruptive promise of vision-based AI in manufacturing. The evidence indicates that AI contributes to the improvement of defect detection, predictive maintenance, and human-robot cooperation, which eventually leads to the restructuring of the organization and changes the skills requirements of the workforce (Buxmann and Hinz, 2022). Our position is that AI computer vision is helping to boost operational efficiency, but it is also creating a number of socio-economic issues, such as job displacement, algorithmic obscurity and ethical risks. Such findings support the necessity to include the social science lens in strategies of AI adoption. We end our research with the recommendations on striking a balance between efficiency benefits and inclusive labor policies, regulatory policies, and responsible innovation.

INTRODUCTION

The spread of artificial intelligence (AI) has increased the technological change in any industry, and the computer vision is becoming the foundation of automation and robotics. In production, AI-driven vision can enable machine versions to see, understand, and act on their surroundings, redefining the production processes in essence (Zhou et al., 2021). Not only does the vision-oriented AI contribute to the detection of defects and quality control, but also to the predictive maintenance, logistic optimization, and robotics collaboration (Wuest et al., 2016). The technologies enhance efficiency by eliminating mistakes, shortening time, and enabling just-in-time production, thereby transforming the competitive environment of manufacturing in the world (Lee et al., 2018). As a social science, these changes in technology raise crucial questions regarding the effects it has on the organization structure, work force dynamics, and the general trends in economic inequality.

The new developments in research also highlight the increased significance of computer vision in the industries. According to an example, Deloitte (2020) found that 64 percent of manufacturers worldwide are starting AI-driven pilot initiatives, and vision technologies are the quickest advancing ones. Similar results were observed in a survey conducted by McKinsey (2022) which revealed that more than half of manufacturers believed that computer vision was an enabling factor to implement Industry 4.0 because it helped to enhance real-time decision-making and eliminate human involvement in repetitive inspection processes. But even though technical advancements are thoroughly captured in literature, social and organizational impacts have not been theorized. In particular, the effects of automation on the interactions with labor, management hierarchies, and institutional norms have little empirical support (Brynjolfsson and McAfee, 2014; Jarrahi, 2018). It is such an empty state that is especially applicable in the light of the fact that digital technologies tend to solidify, as opposed to eradicating, the existing disparities within the working environment (Zuboff, 2019).

The larger scope of Industry 4.0 also demonstrates the importance of the vision systems based on AI. Industry 4.0 is often referred to as the fourth industrial revolution, combining the concepts of cyber-physical system, IoT (Internet of Things), and machine learning into industrial ecosystems (Kagermann et al., 2013). In this context, computer vision does not exist as a vacuum within a socio-technical system with growing collaboration between humans and machines in the workspaces (Duflou et al., 2018). As an illustration, collaborative robots (cobots) with vision technologies are built to be able to securely share the work with human workers, with potential productivity improvements with potential displacement of skills and human autonomy threats (Fleming, 2019). Such tensions render it necessary to place the technical innovations in the wider institutional and organizational context.

On policy, the European Commission (2021) has highlighted the duality of AI in improving industrial competitiveness and imperative safeguards to address human-centric implementation. In the same spirit, the World Economic Forum (2020) has opined that the application of AI in the manufacturing sector has to be both efficiency and workforce-inclusive to prevent the aggravation of structural unemployment. In the case of developing economies such as those found in South Asia, the spread of computer vision technologies may intensify their reliance on the global supply chain and at the same time create possibilities of technological modernization (Siddiqui, 2021). Therefore, the issues of equity, governance, and control are the core of the determination of the societal impact of these innovations.

The scholarly discussion is rapidly coming to the point of interdisciplinary approaches. Technologists focus on the progress of algorithms in deep learning structures that drive contemporary sighted systems (He et al., 2016; Li et al., 2022), and scholars of organization look at how digital technologies transform managerial practices and labor relations (Jarrahi, 2018; Acemoglu and Restrepo, 2020). In particular, Acemoglu and Restrepo (2019) show that some groups of employees may lose their jobs to automation despite the creation of new jobs, and the overall impact is a matter of institutional adjustment and reskilling. This is to say that, although defect detection and predictive maintenance will perhaps lessen the need to use manual inspection, they will create the demand of novel types of technical knowledge in data labeling, system oversight, and algorithm auditing.

The key research question of this article is the following: How will AI-enabled computer vision transform manufacturing and robotics, and what are the larger social and organizational implications? The study addresses the issue by conceptualizing it in terms of both technical and social science in the sense that the adoption of technologies is not only about efficiency but values, power, and governance.

The paper aims have threefold goals: (1) to survey current literature, technological and social science on AI-powered vision in industries, (2) to examine the socio-technical consequences of its use, and (3) to outline gaps to the future cross-disciplinary research. This work is part of a growing discourse at the nexus of AI, work, and society by placing technical developments in their larger social context. In the end, the interpretive possibility of computer vision can only be learnt by relying not only on engineering insight as it exists in the present but also by critically examining its ethical, economic, and organizational aspects.

LITERATURE REVIEW

Computer vision is a field of study that has an equal component of both technical and social aspects as well as organizational aspects of the research as it is both a technological facilitator and a social disrupter. The theory of deep learning, especially convolutional neural networks (CNNs), set the stage of new achievements in image classification and object detection (Krizhevsky et al., 2017; LeCun et al., 2015). These developments played a critical role in transforming computer vision in the context of academic research to industrial real world use. CNNs have gained extensive applications in manufacturing environments (defect recognition and anomaly detection) and in process optimization (Patel et al., 2019).

Based on such roots, future studies have utilized vision-based AI on industrial issues. As an example, machine vision models have been effectively adapted to automated quality inspection, such that micro-defects that cannot be detected by inspectors can be detected with almost perfect accuracy (Li et al., 2021). Algorithms of reinforcement learning also enable robotic systems to adjust themselves to dynamic environments that maximize efficiency with minimal downtime (Silver et al., 2017). The latest research on digital twins also revealed the opportunity of integrating real-time computer vision with the cyber-physical system that would facilitate predictive maintenance and monitoring of processes (Qi and Tao, 2018; Zhang et al., 2020).

Most recently, a new version of cloud and edge-based vision is implemented to enhance supply chain visibility, allowing real-time tracking of production processes and stocks in globalized production chains (Buxmann & Hinz, 2022;

Xu et al., 2021). This is in line with larger Industry 4.0 paradigms that focus on data-oriented manufacturing as computer vision is not only an inspection instrument but a fundamental facilitator of smart factories (Kagermann et al., 2013; Lee et al., 2018).

Vision systems are also very closely related to robotics research. Research in autonomous robotics highlights the importance of the AI-based perception to enable flexible automation, including collaborative robots (cobots) capable of detecting and reacting to human workers (Siciliano and Khatib, 2016; Kruger et al., 2019). Such abilities are especially essential within such industries as automotive and electronics where work performance is highly detailed and flexible.

Through all these technical advances, social science studies have directed interest to the wider organizational and social consequences of computer vision in industry. One of the issues of interest is the labor restructuring. Historically, automation has substituted some type of labor and generated other varieties of high-skilled work, which only worsens inequality (Autor, 2015; Acemoglu and Restrepo, 2018, 2020). This trend is being increased by vision-based automation that replaces the tasks that were traditionally considered to be the tasks that presuppose human judgment of perception, including quality inspection and assembly monitoring (Fleming, 2019).

Moreover, there are new challenges of algorithmic opacity. The authors present an argument that, due to the black box characteristics of machine learning frameworks, workers and managers cannot be able to understand or challenge decisions made by AI (Burrell, 2016). Such a transparency creates ethical and governance concerns especially after vision-based systems are deployed to spy on workers or measure their efficiency (Zuboff, 2019; Kellogg et al., 2020). The issue of surveillance and data privacy has also been noted in the critical social analysis of digital manufacturing (Sadowski, 2020).

Organizational scholars refer to the fact that technical accuracy is not the only factor in the successful implementation of the computer vision. It takes managerial trust, acceptance of workers, and conformity to the norms of the institution (Jarrahi, 2018; Faraj et al., 2018). Workers may present resistance in the event of the perceived threat of job security or autonomy due to the adoption of technologies (Frey and Osborne, 2017). However, when positioned as an addition, but not a replacement of human labor, computer vision systems can translate into collaborative situations where machines and humans can be complementary (Wilson and Daugherty, 2018).

Although the performance measures of accuracy, latency, or throughput are commonly used as the technical aspects of computer vision application (He et al., 2016; Li et al., 2022), comparatively scarce literature directly considers the socio-organizational consequences of computer vision usage. The literature is also quite divided: engineering studies focus on technological viability whereas social science literature tends to criticize automation in general without paying enough attention to the particular affordances of vision-based AI.

It is interesting to note that empirical studies on the reconfiguring of organizational decision-making structures by computer vision are deficient. To illustrate the point, predictive maintenance systems can transfer power of human supervisors to algorithmic models, which changes accountability chains in companies (Shrestha et al., 2021). Equally, there is an absence of data on the potential effects of various regulatory regimes on ethical application of industrial computer vision, even as AI governance is increasingly gaining global attention (European Commission, 2021; Nemitz, 2018).

The other gap is inequality by region. Whereas computer vision is fast becoming a common practice among multinational corporations, small and medium enterprises (SMEs) in the Global South do not have the resources to implement such systems (Siddiqui, 2021). Such unequal distribution threatens to further increase economic disparities and dependence in the international supply chains.

In order to overcome these gaps, researchers propose the interdisciplinary methodology that would overlap technical innovation with social investigation (Jasanoff, 2016; Wajcman, 2017). Social science theories like the socio-technical systems theory and critical algorithm studies may be used to explain how computer vision technologies are co-produced by human, organizational, and regulatory actors. Similarly, organizational ethnographies of smart factories may shed more light on the ways workers experience and bargain the process of integrating the vision-based AI in their day-to-day activities.

This article will be a part of this growing discourse where technical evidence of AI-driven computer vision is made to make contact with critical social science views. By so doing, it not only addresses the opportunities and risks associated with these technologies in industrial settings, but provides a more comprehensive description of how they might affect manufacturing, robotics, and the society.

METHODOLOGY

In this research, the methodology will be qualitative meta-synthesis, which is a recognised research approach to combine findings of numerous qualitative studies in order to produce new meanings and conceptual knowledge (Noblit and Hare, 1988; Finfgeld-Connett, 2018). In contrast to conventional literature review, which summarizes research, meta-synthesis reinterprets primary studies in a systematic manner in order to come up with a more detailed explanation of multifaceted phenomena. Such a method would be especially effective in exploring the socio-technical inscriptions of artificial intelligence (AI) and computer vision and its application to the organization and society in general.

The evaluation is based on secondary data gathered (more than 60 sources) of peer-reviewed journal articles, industrial cases, and organizational reports. The databases that were used to identify peer-reviewed articles include Scopus, Web of science, and IEEE Xplore, which made the materials scholarly. Consulting firm (e.g., McKinsey and Company, 2022) as well as policy organization (e.g., European Commission, 2021) industry reports were also used to capture a real-world view of implementation. The examples of companies that use AI-based vision systems in the manufacturing field provided some background information about the ways in which technical capabilities are turned into organizational processes.

Inclusion criteria were based on the studies that answered at least one of the following dimensions:

AI algorithms and computer vision models (ex: CNNs, GANs, reinforcement learning).

Manufacturing and robotics such as quality inspection, predictive maintenance and collaborative robotics.

Automation socio-economic impacts especially on labor, organizational behavioral change, and moral issues.

The tripartite choice guaranteed the balance of technical performance evaluations and the socio-organizational understanding so that the study could address disciplinary silos.

Thematic coding strategy was used in order to synthesize data (Braun and Clarke, 2006). In a sequence of inductive coding, textual sources were coded in terms of recurring patterns of three broad themes: (1) efficiency and productivity gains, (2) labor restructuring and workforce dynamics and (3) ethical and governance implications. This methodology is compatible with what other scholars have done in qualitative synthesis methods, and aimed to find cross-cutting themes, but still maintained the sensitivity to the contextual variations (Thomas and Harden, 2008).

In the technical sphere, critical importance was given to the major AI models that are popular in computer vision. Image classification and object detection in industry continue to rely on Convolutional Neural Networks (CNNs) (LeCun et al., 2015; Krizhevsky et al., 2017). GANs have also been used to generate synthetic defects and to augment data, overcoming constraints of small industrial data sets (Goodfellow et al., 2016; Frid-Adar et al., 2018). The reinforcement learning methods were examined in terms of their contribution to adaptive robotic systems that can learn in dynamic production settings (Silver et al., 2017; Mnih et al., 2015).

The selection of the qualitative meta-synthesis was informed by the desire to both identify technical standards and organizational stories. The performance metrics usually highlighted in quantitative meta-analyses include model accuracy or defect detection rates (He et al., 2016; Li et al., 2021). Nevertheless, these solutions do not consider the ways in which these technologies transform the work of humans, organization, and ethical standards (Jarrahi, 2018; Shrestha et al., 2021). In comparison, qualitative synthesis enables incorporation of various types of evidence- such as ethnographic descriptions, management research, and industrial reports- into a complete evaluation.

Moreover, the approach reacts to the swift changing character of AI studies, with new models and industrial usages being developed on a regular basis (Jordan & Mitchell, 2015).

The cross-disciplinary synthesis of results is helpful in preventing technological determinism since it places new innovations in the context of a broader socio-economic and regulatory environment (Wajcman, 2017).

Coding was done repeatedly to increase the reliability and constant comparisons were made across sources to keep thematic categories valid (Glaser and Strauss, 1967). Triangulation has been reached by considering the insights of various areas engineering, organizational studies, and policy analysis and ensuring a strong element of validity (Flick, 2018). The ethical issues were considered by ensuring that the academic standards of integrity were followed and all the data presented were obtained through the verifiable and credibly cited sources.

Such methodological design, which includes rigorous selection of the literature coupled with systematic thematic synthesis is appropriate regarding the interdisciplinarity of the research question. Through a synthesis of technical and social science literature, the research not only traces out the current state of AI based computer vision in manufacturing and robotics, but also points out its organizational, ethical, and societal implication.

RESULTS AND EVALUATION

We synthesize three findings that can be interrelated regarding the role of AI-supported computer vision in manufacturing and robotics: (1) operational efficiency, (2) restructuring of the workforce, and (3) socio-ethical implications. Every sphere consists of technical success as well as general organizational and social outcomes.

Vision systems powered by AI will always out perform the conventional inspection mechanisms. Li et al. (2021) discovered that the accuracy of defect detection in industrial manufacturing increased by as much as 90% with the convolutional neural networks (CNNs) as opposed to visual inspection by human beings. Such enhancements are not only in defect detection. Predictive maintenance using vision has decreased unexpected down time of equipment by 30-40 percent, decreasing maintenance expenses and increasing the lifespan of the equipment (Zhang et al., 2020). This is also the case with McKinsey & Company (2022) which estimated annual savings of up to half a trillion in manufacturing industries worldwide with the use of AI-enhanced predictive maintenance.

Through the combination of reinforcement learning and real-time vision information, throughput increases even further, as robots adjust to a changing environment minimizing delays and shortening cycle time (Silver et al., 2017). Case studies of Industry 4.0 also indicate that the vision provided by AI may increase supply chains transparency, allowing real-time monitoring of the components and minimizing production bottlenecks (Buxmann & Hinz, 2022). These conclusions prove that AI-based vision is one of the pillars of efficiency-oriented changes that have been implemented in contemporary manufacturing.

The efficiency gains have exigent implications to labor. Autor (2015) and Acemoglu and Restrepo (2018) show that automation displaces low- and mid-skill jobs more than other types of jobs, especially routine inspection and assembly positions. The case studies on European automotive industries reveal that the number of jobs in quality-control by hand significantly decreases, and instead, the number of jobs, which demand knowledge of data science, machine control, and systems integration, increases, but with higher salaries (Duflou et al., 2018).

Nonetheless, restructuring of workforce is not completely substitutional. Brynjolfsson and McAfee (2014) posit that augmentation is the situation where intelligent systems work with human workers, and they use examples of cobot (collaborative robot) when computer vision helps humans in the intricate task, such as precision assembly. According to Deloitte (2020), 74 percent of manufacturers say they expect to train its workers in the next five years, reflecting a change in the workforce towards manual work to more digitally literate and algorithmically controlled work.

The unequal share of benefits is also very important. According to research by Jarrahi (2018), the concentration of the decision-making roles is becoming more concentrated in the hands of high-skill technical personnel that may cast doubts on the increased income inequality. In the absence of active reskilling measures, such a transition threatens to widen labor market inequalities (Frey & Osborne, 2017).

In addition to efficiency and labour dynamics, our synthesis raises acute socio-ethical issues. Burrell (2016) underlines the lack of transparency in quality control and predictive maintenance due to the lack of transparency in the operation of algorithms in terms of decision-making. Accountability gaps normally exist because workers and managers are unable to completely comprehend or challenge machine judgments. This is in line with Shrestha et al. (2021), who discovered that AI-based decision structures diminish the autonomy of employees and place control in the hands of algorithmic outputs.

Another controversial question is surveillance. The idea of a surveillance capitalism presented by Zuboff (2019) sounds a bit familiar to manufacturing industries where vision cameras can see the movement of workers and their achievements. According to a study done on workplace monitoring by Ball (2010), it is true that the higher the surveillance the less will be the trust and morale of the employees. These results imply that although AI-based vision provides organizational control, it also creates the conflicts related to privacy and autonomy.

There is still the underdeveloped ethical and regulatory frameworks. The three points described by the European Commission (2021) explainability, human oversight and fairness are critical features of industrial AI, but they fall behind on practice. On the same note, Wajcman (2017) observes that the automation discourse tends to focus more on the technical potential and less on the practical lives of employees. The absence of normal explainability instruments of industrial computer vision demonstrates the urgency of cross-disciplinary research across the boundaries of technical design and ethical governance (Samek et al., 2019).

Our results are consistent with available technical work, but they go further to provide knowledge on organizational and ethical levels. Technically, the reported efficiency gains fall in line with the benchmarks formed by He et al. (2016) in the context of deep residual learning and Krizhevsky et al. (2017) in the context of CNN-based image classification. Most of the performance advances achieved in industrial defect detection and predictive maintenance rely on the use of these technologies.

Our results, on the organizational front, support the literature on labor restructuring brought about by automation (Autor, 2015; Acemoglu and Restrepo, 2018). But they also demonstrate a gap in social science research on the way in which algorithmic vagueness and organizational surveillance alters organizational cultures. Social science views unveil the latent costs in autonomy, trust, and equity, unlike technical ones with their focus on accuracy and latency (Jarrahi, 2018; Zuboff, 2019).

The analysis indicates that AI-based computer vision is not only a technical solution, but a socio-technical system with extensive implications. The results of efficiency are well-reported and can be predicted, whereas workforce restructuring and socio-ethical questions need to be addressed more empirically and theoretically. It will be necessary to bridge these areas to ensure that there is a balanced adoption that will maximize organizational gains and also reduce risks to both labor and the society.

DISCUSSION

The results of the current research point to a two-sided change that AI-driven computer vision implementation in manufacturing and robotics entails. Technical outcomes show, on the one hand, considerable productivity gains, accuracy, and forecasting possibilities. As an example, the detection of defect rates at 90% and a reduction in downtime by 30-40 percent (Li et al., 2021; Zhang et al., 2020) demonstrate how technologies can make a company more competitive, streamline the organizational processes, and improve the supply chains worldwide. The findings echo the previous studies which accentuate the productivity-enhancing power of digital technologies in the industrial context (Brynjolfsson and McAfee, 2014; McKinsey and Company, 2022). Conversely, the results also reveal the breach in labor markets, ethical issues with surveillance and obscurity, and governance dilemmas related to the implementation of machine decision-making in the business operations. This dichotomy bolsters the soci-technical paradigms that emphasize intertwining of technical structures and the social practices (Orlikowski, 2007; Trist, 1981).

In the labor sense, our synthesis confirms that there is job polarization. The number of manual inspection tasks performed every day is on the decrease, and the positions with high skill expectations in data science, systems integration, and algorithm management are in demand (Autor, 2015; Acemoglu and Restrepo, 2018). This resembles the more general skill-biased technological change thesis, that states that digital technologies are disproportionately advantaging workers who possess high levels of technical expertise (Goldin and Katz, 2009). However, although the beneficial effects of efficiency are undeniable, they are unequally distributed, with the tendency to increase the already existing inequalities both inside and outside the organizations (Frey and Osborne, 2017). Unless reskilling is actively undertaken by them, the use of AI-based vision might further increase the digital divide between high- and low-skill employees (Duflou et al., 2018).

Ethical issues are also important. The concept of algorithmic opacity by Burrell (2016) highlights how hard it is to explain the reasoning of machine choices in machine defect detection and predictive maintenance. It is also common that workers and managers have accountability gaps when the results of AI systems are unexplained or disputed (Shrestha et al., 2021). Simultaneously, the same critique of surveillance capitalism by Zuboff (2019) applies to manufacturing, where vision systems track the products as well as the movement or performance of the employees. This poses a danger of excessive surveillance and de-autonomizing of workers, which is supported by research that reveals that surveillance leads to less trust and job satisfaction (Ball, 2010).

Such results indicate that there is a need to implement governance structures that are more efficient and ethical at the same time. According to the Artificial intelligence Act prepared by the European Commission (2021), transparency, human oversight, and accountability are the key principles of trustful AI in industrial spheres. Nonetheless, application is still not widespread, particularly in non-advanced economies. Cross-national comparisons would thus be useful in determining the role of institutional and policy contexts in defining the adoption and ramifications of industrial AI (Coe and Yeung, 2015). As an illustration, whereas the Industrie 4.0 policies of Germany focus on the involvement of workers in digital transformation, in emerging economies, the policies of worker protection remain underdeveloped.

This research has a weakness in the methodology as it uses secondary data. Although meta-synthesis offers an overlay of technological, organizational and ethical aspects, it does not have a fine-grained framework as primary fieldwork. The emerging studies must also include ethnographic techniques to help understand how workers lived through the process of adjusting to the AI-enabled worlds (Suchman, 2007). In a manner that might not necessarily reflect in managerial stories, the role of ethnographies could be to reveal how workers are resisting, re-defining, or re-using computer vision technologies. On the same note, longitudinal case studies may trace the rising trends of the organizational cultures with the advent of AI in daily practices.

The need in responsible innovation is interdisciplinary, dialogic. The balance between efficiency and labor rights presupposes not only efficient design but also protective institutions, such as social dialogue among the employers, the employees, and the regulators (Wajcman, 2017). The explainable AI frameworks (Samek et al., 2019) can be used to facilitate algorithmic transparency, whereas human-in-the-loop systems (Jarrahi, 2018) may help to maintain worker autonomy. Notably, governance is not to be regarded as a kind of restriction but as a facilitator of the sustainable innovation that promotes not only productivity but also social well-being.

To sum up, computer vision that is powered by AI is a chance and a challenge. It alters the ways of manufacturing processes more efficiently than it has ever happened, but also re-orients the labor markets, provokes ethical issues and challenges the systems of governance. The interpretation of this duality requires socio-technical insights that place technology into context of its greater organizational and social contexts. Technological evidence and social science understanding can guide scholars and practitioners to wade through the opportunities and dangers of this technological edge.

CONCLUSION

Computer vision is changing the future of manufacturing and robotics with AI-powered system perception, interpretation, and reaction to complex environments to a degree never before seen. Its practical usefulness is also supported by empirical data: the rate of defect detection in industrial inspection activities is now higher than human standards, and predictive maintenance can considerably decrease the downtime of equipment (Li et al., 2022; Zhang et al., 2020). Not only do these innovations simplify the efficiency of operations, but also expand the area of robotics to adaptative, collaborative areas and thereby redefine the production systems and the global supply chains (McKinsey & Company, 2022).

However, in parallel with these developments is another cluster of significant social and organizational consequences. Research is constantly showing that automation is reshaping the labor markets, usually crowding out the low-skill, low-technology jobs, but creating high-skill, technology-centered jobs (Autor, 2015; Acemoglu and Restrepo, 2018). This dynamic also helps create what scholars have termed as the job polarization where the fruits of productivity increases are not equally shared, which strengthens economic inequalities (Frey and Osborne, 2017). Ethical issues also make it more complex because the lack of visibility in AI system decision making makes it problematic in the areas of responsibility, surveillance and worker autonomy (Burrell, 2016; Zuboff, 2019).

The results of this paper reaffirm the importance of socio-technical paradigms by placing technology development in wider institutional and cultural systems (Orlikowski, 2007). In such a way, it will be possible to achieve a balance between the benefits of efficiency and social protection with such a result that workers, managers, and policymakers also contribute to the course of innovation. Re-training, involvement in governance, and regulation, i.e. as proposed in the European Union AI Act (European Commission, 2021) can be used to reduce risks, and increase trust in industrial AI.

The use of secondary data in this study also implies that there are limitations that should be overcome in upcoming research. Specifically, ethnographic and longitudinal research might offer an understanding of the experience of workers in AI-enabled settings; and comparative research interventions at national levels may shed light on the role played by various policy regimes in mediating the impact of automation (Jarrahi, 2018). These methods would add value to existing discussions by anchoring the technical results on organizational and societal actualities.

To sum up, the AI-driven computer vision represents a two-sided change. It is not just the eyes of future, which are going to drive industrial structures to even greater efficacy but also a mirror of the ethical, social and economic decisions that societies will need to face. The interdisciplinary cooperation between computer science, management studies, labor economics, and ethics will be necessary in making sure that these technologies are used towards sustainable development. It is solely through the inclusion of social factors in technical innovation that we can make sure that the future of manufacturing and robotics lies not only more fruitful, but also fairer and more human.

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