

The impact of automation on manager roles

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Abstract: The effects of technological progress are increasingly evident in the world of industrial manufacturing companies. These changes affect the competitiveness and day-to-day operations of companies, even if the spread of fundamental changes throughout the supply chain is sometimes challenged by safety and other administrative regulations. The question arises: does this technological change affect the tasks of managers in these companies? Therefore, this study examined the extent to which the degree of automation of other actors involved in a given task plays a role in basic managerial tasks and whether this affects the work of managers in performing their managerial responsibilities.

Keywords: *human-machine system, production, cyborg, industry 4.0, digital transformation, automation*

JEL Codes: *O33, L23, M11*

Introduction

The rise of automation in manufacturing companies is a response to the shortage of skilled labor and the need to increase efficiency. However, the cooperation between human-machine and machine-machine systems raises challenges in terms of trust and culture. The aim of this publication is to present the transformation of companies, explore the conditions for collaboration between humans and machines (Alhaji et al., 2020), and analyze the cognitive biases (Földesi & Sós, 2024; Sós et al., 2023) that arise during automation. With the emergence of automated systems and the spread of human-machine and machine-machine systems, new challenges arise in the coordination of corporate operations (Dröder et al., 2018; Geng & Varshney, 2022), which

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need to be studied in order to achieve results. The research highlights how the evolution from the human factor to autonomous systems affects decision-making, corporate structures, and knowledge sharing (Anzalone et al., 2015; Sorrentino et al., 2024). By integrating theoretical and practical approaches, answers are sought to how human-centered companies can evolve into the “cyborg” systems of the future.

In manufacturing companies, the rise of automation is a response to the shortage of skilled labour and the need to increase efficiency. However, the interaction between human-machine and machine-machine systems raises challenges in terms of trust and culture. The aim of the paper is to describe how companies are transforming, explore the conditions for human-machine collaboration, and analyze the cognitive biases (Dobelli & Griffin, 2013; Kahneman, 2011; Sibony, 2020) that arise during automation.

Automation bias is the phenomenon whereby people place excessive trust in machines and automated systems. As a result, they tend to ignore errors or contradictory information provided by the system (Goddard et al., 2011). This can cause serious problems, the scale of which can be reduced in two ways. On the one hand, by creating more robust, accurate, and less error-prone systems. On the other hand, it ensures that the human members of the organization acquire more precise and profound knowledge about how the technology works. With the appearance of automated systems and the spread of human-machine and machine-machine systems, new challenges arise in the coordination of corporate operations, which must be studied in order to achieve results (Glas & Pelachaud, 2015).

The concept of a company has changed significantly over time. In 1938, Chester Barnard (Barnard, 1962) defined a company as “a system of intentionally coordinated activities or forces of two or more humans.” In 1980, Caves defined a company (Richard E Caves, 1980) as “a legal-economic entity that coordinates resources for a specific purpose, usually profit.”

It can introduce a significant change between the two definitions. Barnard (Barnard, 1962) still demonstrates a company as a collaboration between people, but this later shifted toward grouping resources for specific purposes.

The word “human” was removed from the definition, and this trend has only grown stronger since then. Have we reached a level of development where machines not only assist but also replace humans as the main source of added value? In other words, processes have emerged and become significant in which the owner is involved:

- Machine activity assisted by humans.
- Fully autonomous machine activity.

From a senior management perspective, this presents new challenges. If the theory is correct, then it is not only necessary to organize interactions between people and organize resources based on human decision-making and behavior, but it is also necessary to understand the system and operating principles of machine-based activities (Acemoglu & Restrepo, 2018), as well as the challenges that arise from coordinating systems built on different logical bases. These “cyborg organizations” – due to their half-human, half-machine nature – require new knowledge from strategic decision-makers (Waschull et al., 2020).

This publication aims to investigate the transformation of manufacturing companies driven by the increasing adoption of automation technologies. Specifically, the research seeks to identify the organizational and cognitive conditions that enable effective collaboration between humans and intelligent systems (Leyer & Schneider, 2021; Xu et al., 2020), and to analyze the cognitive biases that arise during the process of automation. By integrating theoretical perspectives with empirical insights, the study aims to contribute to a comprehensive understanding of how human-centered enterprises evolve toward hybrid socio-technical systems in which human and machine agents jointly participate in decision-making and value creation.

The research results demonstrate that automation not only increases efficiency, but also fundamentally transforms the structural foundations of organizations. The research identifies automation bias and other cognitive biases in automated environments as significant factors influencing managerial decision-making (Földesi & Sós, 2023; Van Doorn et al., 2023). Ultimately, the research provides a theoretical and practical framework for understanding and managing the coexistence of human and autonomous systems in the changing industrial production environment.

The concept of automation and levels of cyborgization

To understand automation, it is first necessary to define the concept: “A corporate structure in which, in addition to processes based on human labour, autonomous machine- and technology-driven processes, separate from those processes but interacting with them at the usual process connection points,

perform clearly definable, independent steps of value-creating activities”.(Cummings, 2004)

When talking about autonomous execution, the processes referred to are those whose “level of automation” (LOA) reaches five or higher on the scale defined by M.L. Cummings. The level of assurance (LOA) is a term used in the field of computer security to describe the degree of trust placed in the identity of a person or organization.

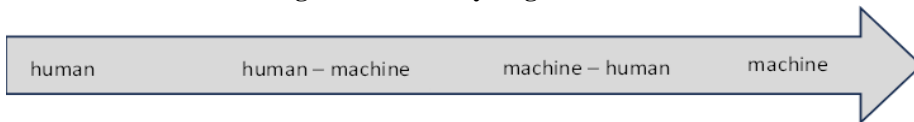
Table 1. Levels of automation according to M.L. Cummings (Cummings, 2004)

Auto- mation level	Automation description
1	The computer offers no assistance: humans must make all decisions and actions.
2	The computer offers a complete set of decision/action alternatives, or
3	Narrows the selection down to a few, or
4	Suggests one alternative, and
5	Executes that suggestion if the human approves, or
6	Allows the human a restricted time to veto before automatic execution, or
7	Executes automatically, then necessarily informs humans, and
8	Informs the human only if asked, or
9	Informs humans only if the computer decides to do so.
10	The computer decides everything and acts autonomously, ignoring the human.

Based on these levels, a given company process can be placed on the following scale (de Andrés-Sánchez et al., 2024):

- Human: Uses human resources to achieve the desired result
- Human–machine: Relies primarily on human resources, supported by machine solutions
- Machine-human: The goal is mainly achieved through automated solutions, but human involvement is necessary
- Automated: A fully automated solution achieves the desired effect

Figure 1. Process cyborgisation scale



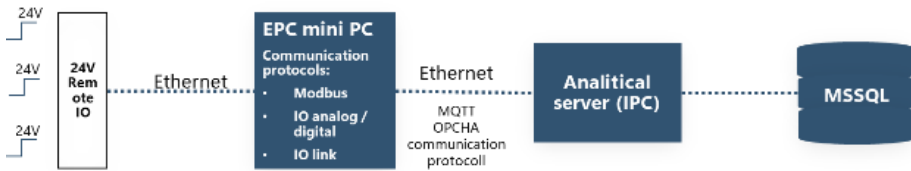
(Source: own compilation based on (de Andrés-Sánchez et al., 2024))

Therefore, a cyborg organization can be defined as one in which a significant portion of processes are performed by highly automated non-human systems on the above scale. Further research needs to address the detailed elaboration of this scale and the background of the placement of resource groups responsible for individual processes.

Methodology

While preparing this study, it was based on three sources. The first is data from direct production, which was generated in the field, that is, during organizational development work carried out at a Tier 1 automotive manufacturing company. Schematic diagram (Figure 2) of data generation made by an industrial project by the Hunify Laboratories:

Figure 2. Schematic diagram of an automated data collection system



(Own compilation made by an industrial project (Hunify Laboratories, 2025))

The conclusions and other professional information are based on our own observations and interviews with industry organizational development experts, top managers, and operational managers.

Limitation: The research's examples are based on our industrial and manufacturing experience. They may appear differently in other contexts and/or industries.

Analysis of the managerial responsibilities in the decision-making process

When examining human-machine systems and introducing machine-machine systems, it is important to understand the role of the manager, as the role played by the manager is crucial in terms of decision-making.

According to Mintzberg (Mintzberg, 1973) managerial responsibilities can be divided into three categories and ten subcategories. The table below describes these tasks and whether the nature of the entity involved in a given task influences the skills and interactions required for the manager to perform the task.

Table 2. The impact of the nature of entities on leadership roles

<i>Categories</i>	<i>Sub-Categories</i>	<i>Description</i>
Interpersonal Roles	Figurehead	The manager serves as the formal representative of the organization, performing ceremonial and symbolic duties such as signing contracts and attending official events.
	Leader	The manager motivates, supports, and develops employees, fostering team cohesion and ensuring staff work effectively.
	Liaison	The manager builds and maintains relationships with both internal and external stakeholders to facilitate information flow and collaboration.
Informational Roles	Monitor	The manager observes the organization and its environment to identify changes, opportunities, and threats.
	Disseminator	The manager shares important information internally to ensure employees have the knowledge necessary for their tasks.
	Spokesperson	The manager communicates the organization's position, strategy, and achievements externally to partners, customers, and other stakeholders.
Decisional Roles	Entrepreneur	The manager initiates new projects, drives improvements, and fosters innovation within the organization.
	Disturbance Handler	The manager addresses conflicts and unexpected issues, ensuring smooth operations.
	Resource Allocator	The manager effectively distributes time, money, workforce, and other resources to meet organizational objectives.
	Negotiator	The manager acts on behalf of the organization during negotiations with partners, clients, and other external parties.

Source: Own compilation based on Mintzberg (Mintzberg, 1973)

Each category and subcategory must be examined to determine who the fundamental subjects or instruments of the given activity are, and whether

the human or mechanical nature of these actors influences the nature of the interaction.

Interpersonal roles (Mintzberg, 1973)

Figurehead – Symbolic and legal acts are, by their very nature, human activities. Here, automation and machine tools can only appear as auxiliary tools, such as marketing tools, PR techniques, and information distribution systems.

Significance of machine systems in this role: low.

Leader – Machines do not need motivation or a sense of belonging. Machine solutions can appear as tools, such as systems that facilitate the work of employees, but they are not essential actors in the execution of activities (Gómez-Virseda & Usanos, 2021).

Significance of machine systems in this role: low.

Liaison – This activity refers more to the informal flow of information. Obtaining and managing strategic-level information and maintaining such relationships is an interpersonal task. From this, we can conclude that the number of interactions with cyborg systems is particularly low when performing interpersonal leadership roles. This area is the classic primary or representative role, which will typically remain the domain of humans for the foreseeable future.

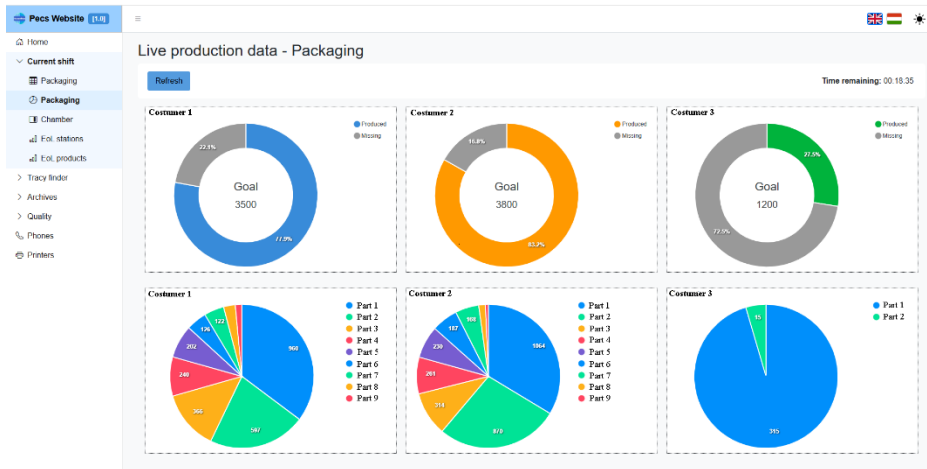
Significance of machine systems in the role: low.

Informational roles (Mintzberg, 1973)

Monitor – This subcategory involves the collection and systematization of external and internal data and the identification of trends that can be read from it. These are areas in which machine solutions far surpass human-based systems in terms of speed, capacity, and reliability. This is an area where knowledge of the functioning of machine resources is essential. Figure 3 shows a live production data display based on a real, complex data collection system. The company where the data was collected cannot be named, and the customer data and component names are not public, so they have been redacted in this publication. This is a typical example of how managers make decisions based on the data visible on the monitor, i.e., based on machine activity.

Significance of machine systems in this role: high.

Figure 3. Management tool displaying live production data

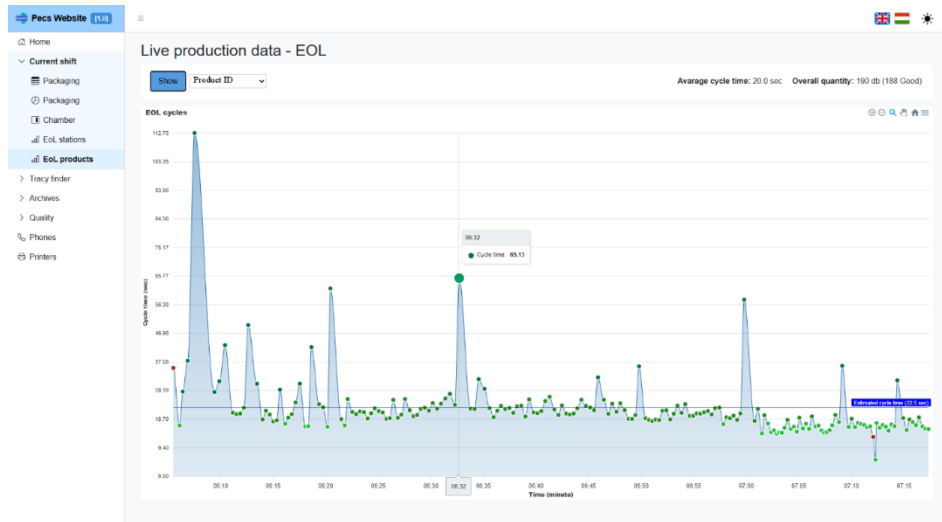


(Primary data from production support software,
Software programmed by: Ráhel Erdősi, Kristóf Pálfalvy)

Disseminator – Information must not only be organized, but also communicated and interpreted. Automated systems perform better than human solutions in this regard as well. Properly organized information can be delivered much more efficiently to the necessary places, whether the recipient is human or machine. The manager's task here is to determine the distribution routes and the quality of the information to be conveyed. When the appropriate LOA level is reached, the response to the given information can also be automated. For example, two automatic triggers have been set in the live production data below. One is an alert system that sends a report to management if the cycle time of a product significantly exceeds the expected level. (See Figure 4 for the vertical columns that exceed the blue horizontal line.) In this case, it is possible to intervene quickly or perform a root cause analysis later. The other automatic intervention point is when the system detects that the measured physical characteristics of two or more consecutive products are unsatisfactory. In the case of the data shown in Figure 4, the vertical columns that exceed the blue horizontal line indicate data that is not good in terms of time, while the red dot indicates a value that is not good in terms of quality. In this case, the system stops production and notifies the relevant parties, forcing intervention.

The importance of machine systems in the role: high.

Figure 4. Cycle time monitoring system



*(Primary data from production support software,
Software programmed by: Ráhel Erdősi, Kristóf Pálfalvy)*

Spokesperson – The targets for communicating results are humans. Data communication channels can be automated systems, such as production data, plan fulfilment status on the production line, etc. However, these do not completely replace front-line data communication, but they can reduce its efficiency and workload. With a sufficiently large sample, the communication strategy and methods can also be automated by analyzing the responses.

Significance of machine systems in the role: medium.

Overall, machine solutions can play a very important role in two of the three subcategories of the informational role. This allows them to largely replace all steps of management work and the preparatory processes necessary for its completion (data collection, analysis, visualization) and to execute pre-determined decisions affecting direct value-creating processes based on specific parameters.

Decisional roles (Mintzberg, 1973)

Entrepreneur – The tasks belonging to this subcategory can be divided into two parts. One is the production and management of data and correlations

necessary for decision preparation (Bradley, 2017). This is typically the domain of highly automatable and very efficient machine solutions. The other is project implementation. Since the vast majority of measures aimed at increasing efficiency either include automation solutions or are specifically designed for this purpose, the managerial competence required for the new systems to be created is knowledge of their operating principles, limitations, and requirements.

Significance of machine systems in the role: high.

Disturbance Handler – In problem solving, the nature of the manager's task is determined by whether the parties involved in the problem are human or machine entities. If one or more parties are machine entities, effective problem-solving requires deciding whether problem-solving from a machine or human perspective is more effective. To do this, you need to know both solutions' advantages, disadvantages, and costs.

Significance of machine systems in the role: high.

Resource Allocator – Resources can be allocated in an operational or strategic manner, but in both cases, the quality of the data used to prepare the decision determines the effectiveness of the decision (Simon, 1990) However, according to bounded rationality, managers will not take all factors into account. Therefore, if a large amount of data and facts are properly organized, a larger amount can be considered, fundamentally influencing the result.

Significance of machine systems in the role: high.

Negotiator – In negotiations with other actors, one of the most important factors is the potential to assert interests. This depends to a large extent on the information we have about the other party's position (Süle & Schunder, 2024) Therefore, automated solutions also play a role in preparing decisions. Another option is to run various simulations to examine the consequences of a possible decision, but the practical application of this is not yet widespread.

Significance of machine systems in the role: medium.

When examining decision-making roles, it is clear that knowledge, use, and quality of automated systems significantly impact the quality of all roles. Therefore, it is essential for managers to be aware of these factors in order to be effective.

As shown in Table 3, the significance of different roles can be classified into different categories regarding knowledge of automated systems.

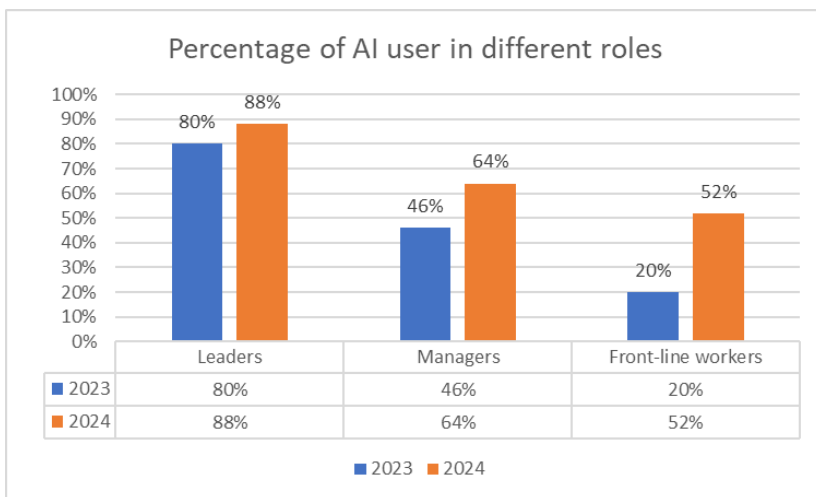
Table 3. Categorization of the significance of roles based on knowledge of automated systems

Significance of machine-based systems	Number of roles	Types of roles
High	5	Monitor Disseminator Entrepreneur Disturbance Handler Resource Allocator
Medium	2	Spokesperson Negotiator
Low	3	Figurehead Leader Liaison

Discussion: Trends in industry and AI penetration

If the above conclusions hold, then this should be reflected in the everyday lives of industry players. Looking at current trends, it is clear that automation is becoming widespread and integrated into everyday management tasks, at least in companies that want to remain competitive. The best indicator of this is to examine the spread of a given solution system and draw conclusions about the overall situation. In addition, AI penetration is also a significant phenomenon.

Figure 5. Percentage of AI users in different roles (BGC, 2024)



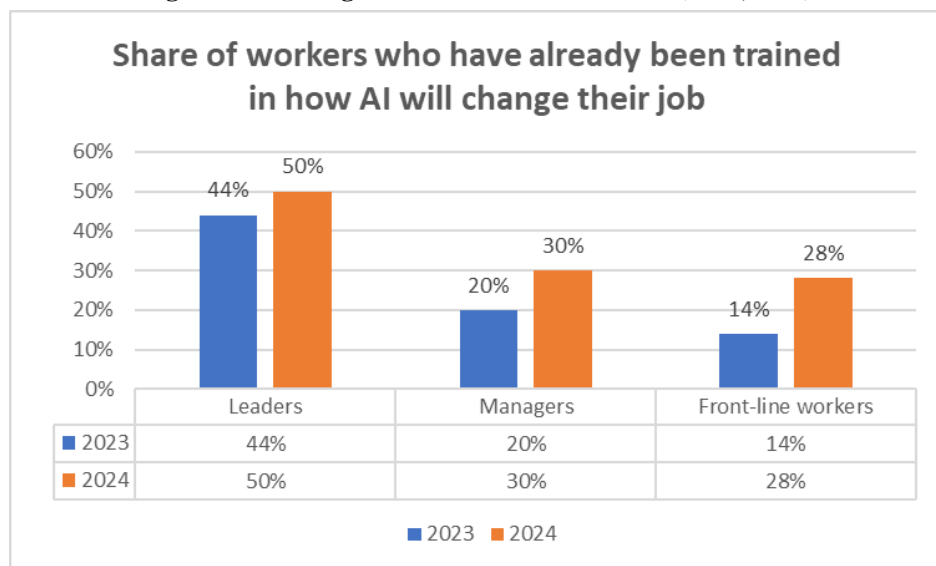
N2023 = 13102
N2024 = 12898

Various AI-based tools are the latest addition to the AI tools revolutionizing the world of work. This has become a serious trend in recent years and has spread explosively in various corporate roles.

As shown in Figure 5, the number of AI users has increased significantly among higher-level employees, but it has also doubled among front-line workers in one year. This means that company employees increasingly encounter machine systems in their daily work and other areas of their lives.

For this reason, it is crucial to examine the extent to which companies consider state-of-the-art tools to be part of their operational strategy. One of the best indicators of this is the amount of effort they put into ensuring that their human employees learn how to use them. Analyzing the data, we see a significant increase in the number of people who have received some form of organized training on the use and effects of AI (Figure 6).

Figure 6. Percentage of AI users in different roles (BGC, 2024)



$N_{2023} = 4404$

$N_{2024} = 4368$

The data demonstrate that the number of people becoming more familiar with the possibilities offered by new technologies is growing significantly.

The managerial roles presented and these trends suggest that companies have recognised and are continuously incorporating modern solutions into their everyday activities, thereby continuously raising the level of automation within

organisations and moving closer to becoming cyborg organisations. This confirms the suggestion that managers need to increasingly consider the demands of technology while performing their traditional managerial tasks and coordinating the work of the organisation's human and machine components.

Conclusion

The research examines the ongoing transformation of manufacturing companies driven by automation and the integration of intelligent systems. There are increasing decision-making situations where managers need to coordinate partially or fully automated systems with human labour. Therefore, the primary goal of this publication is to identify the organizational, cultural, and cognitive conditions that enable effective collaboration between humans and machines, as well as to analyze the cognitive biases that arise during automation processes.

The results indicate that automation not only increases efficiency but also transforms corporate structures, decision-making mechanisms, and the dynamics of knowledge sharing. Trust, transparency, and cultural adaptation are essential for successful human-machine interaction, and for a well-defined set of tasks, the position of participants on the automation scale is significant.

The data demonstrates a significant increase in the number of people becoming more familiar with the opportunities offered by new technologies. These trends suggest that companies have recognized and are continuously integrating modern solutions into their daily operations, thereby continuously raising the level of automation in their organizations and moving closer to becoming cyborg organizations. This reinforces the suggestion that managers need to increasingly consider the demands of technology and how to coordinate the human and machine members of the organization in performing their traditional management tasks. For this reason, this area is worth further investigation, as it confirms the suggestion that, in addition to traditional leadership skills, senior and operational managers must also acquire knowledge of IT systems and understand how to coordinate these systems with traditional, human-centered areas.

The research contributes to the theoretical and practical understanding of cyborg organizations—hybrid socio-technical systems that combine human

judgment with machine intelligence—and provides a framework for managing the coexistence of human and autonomous agents in the future of industrial production.

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