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A Theoretical Evaluation of Smart Production Systems and Industrial Robots within the Context of Industry 4.0[1]

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Abstract

This study comprehensively addresses the role of intelligent manufacturing systems, industrial robots, and dark factories in production processes and the transformation process brought about by Industry 4.0. Today, manufacturers are pressured to produce higher-quality products with shorter lead times. This requirement has necessitated that production systems become integrated, automated, and intelligent. Smart manufacturing creates flexible, responsive and highly efficient production environments using artificial intelligence (AI), internet of things, big data analytics and robotics. Industrial robots have become systems that can not only act on a task basis but also learn, predict, and actively participate in production processes by interacting with humans. In this direction, dark factories are facilities that can produce 24 hours a day without human intervention and offer significant advantages regarding occupational safety, quality and efficiency. However, there are difficulties in the widespread use of these systems, such as high investment costs, applicability limitations in some sectors and the decreasing need for unskilled labour. In conclusion, for the technological opportunities offered by Industry 4.0 to provide sustainable and inclusive benefits, investments incompetent human resources should be increased, education policies should be restructured, and strategic public support should be activated.

Keywords: Industrial Robots, Intelligent Production Systems, Artificial Intelligence

Endüstri 4.0 Bağlamında Akıllı Üretim Sistemleri ve Endüstriyel Robotlar Üzerine Teorik Bir Değerlendirme

Öz

Bu çalışma, Endüstri 4.0'ın getirdiği dönüşüm sürecinde akıllı üretim sistemleri, endüstriyel robotlar ve karanlık fabrikaların üretim süreçlerindeki rolünü kapsamlı biçimde ele almaktadır. Günümüzde üreticiler, daha kısa teslim süreleriyle daha yüksek kaliteli ürünler üretme baskısıyla karşı karşıyadır. Bu gereksinim, üretim sistemlerinin entegre, otomatik ve akıllı hâle gelmesini zorunlu kılmıştır. Akıllı üretim; yapay zekâ, nesnelerin interneti, büyük veri analitiği ve robotik sistemlerin entegre kullanımıyla esnek, duyarlı ve yüksek verimli üretim ortamları oluşturmaktadır.
Endüstriyel robotlar, yalnızca görev bazlı hareket etmekle kalmayıp, insanlarla etkileşime geçerek öğrenebilen, tahmin yürütebilen ve üretim süreçlerine aktif biçimde katılabilen sistemler hâline gelmiştir. Bu doğrultuda

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karanlık fabrikalar, insan müdahalesi olmaksızın 24 saat üretim yapılabilen, iş güvenliği, kalite ve verimlilik açısından önemli avantajlar sunan tesislerdir. Ancak bu sistemlerin yaygınlaşmasında; yüksek yatırım maliyetleri, bazı sektörlerde uygulanabilirlik sınırlamaları ve vasıfsız iş gücüne duyulan ihtiyacın azalması gibi zorluklar mevcuttur. Sonuç olarak, Endüstri 4.0'ın sunduğu teknolojik imkânların sürdürülebilir ve kapsayıcı fayda sağlayabilmesi için, yetkin insan kaynağına yapılan yatırımların artırılması, eğitim politikalarının yeniden yapılandırılması ve stratejik kamu desteklerinin devreye alınması gerekmektedir.

Anahtar Kelimeler: Endüstriyel Robotlar, Akıllı Üretim Sistemleri, Yapay Zeka

Introduction

Globalization has transformed the production sector into a dynamic and highly competitive structure. Manufacturers worldwide have to offer products that both minimize costs and maximize quality to the market in a short time. This situation necessitates orientation towards innovative technologies in production processes and encourages technological transformation in the manufacturing industry (Cheng et al., 2021). One of the most striking developments in this transformation process has been the widespread use of innovative production systems. Intelligent machines, which aim to make production processes more flexible, efficient and responsive, play a critical role in gaining competitive advantage.

Industrial robots, which have an essential place among intelligent machines, have become one of the cornerstones of modern production understanding by providing high productivity, quality and flexibility at low cost (Hägele et al., 2008). Using industrial robots in real production environments offers advantages such as shorter lead times and lower error rates by increasing the agility and adaptability of production systems (Pires, 2007). In this context, the flexibility and speed provided by automation in production processes increase production efficiency and the capacity to respond faster to customer demands (Üster,2024).

Incorporating artificial intelligence (AI) technologies into robotic systems has also been put on the agenda to make these systems more effective, further reflecting technical improvements in the manufacturing area. Its constituent parts, including AI, ML, DL, and big data analysis, allow production systems to acquire intelligence, predictability, and autonomy in decision-making. The idea of Industry 4.0 and the creation of intelligent production systems are underpinned by this convergence of technologies.

Industry 4.0 is a transformation process based on integrating information technologies and production technologies and aims to make production processes more flexible, transparent, integrated and sustainable. Today's business world has to respond to multidimensional needs such as variable customer demands, flexible production requirements, optimized energy use and efficient supply chain management. At this point, smart manufacturing makes it possible to produce high-quality products by optimizing the use of labor, energy and materials at the highest level while also increasing long-term competitiveness (Mehrpouya et al., 2019).

The primary purpose of this study is to examine innovative production systems, which are at the center of contemporary production understanding, within the framework of industrial robots and AI technologies, which are the basic components of these systems. In the research, the structural features of innovative production systems, the advantages they offer, the role of industrial robots in these systems and the contributions that integration with AI can provide will be examined in detail. Thus, the study aims to shed light on reshaping production processes in the digital transformation era.

This study adopts a qualitative and narrative literature review methodology to provide a comprehensive understanding of smart manufacturing systems, industrial robots, and dark factories. The selection of literature was based on peer-reviewed journal articles, books, and reputable conference proceedings published between 2007 and 2024. Databases such as Scopus, IEEE Xplore, ScienceDirect, and Google Scholar were used. Inclusion criteria focused on sources that provided theoretical insights, recent advancements, and applications in the context of Industry 4.0. Studies focusing exclusively on narrow technical aspects without broader

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contextual relevance were excluded. The review aims to synthesize multidisciplinary perspectives by integrating findings from engineering, computer science, and industrial management domains.

1. Artificial Intelligence

The process of digital and technological change that has been experienced from past to present and has affected the entire world causes individuals to change and transform (Şen, 2024). The eld of AI is a significant and quickly expanding branch of computer science that seeks to create intelligent software and systems. While the ultimate goal of AI is to develop systems that can perform tasks usually performed by humans, AI also encompasses the study, modelling, and computerization of intelligence itself. Put another way, AI is an interdisciplinary study of how to make computers capable of learning, reasoning, solving problems, perceiving, and interpreting language (Lu et al., 2012; Min, 2010).

The concept of AI started to resonate in the world of informatics in the 1950s. In this period, the potential of machines to perform complex calculations was characterized as "giant brains", and the existence of systems that could carry out functions similar to human intelligence was seriously discussed for the first time (Roads, 1985). The foundations of AI were laid philosophically and technically with Alan Turing's famous "Turing Test", in which he questioned the potential of machines to think. He became a scientific field by gaining a disciplinary framework with the Dartmouth Conference in 1956.

Researchers in AI have developed a wide range of techniques and tools to address a wide range of complicated problems that traditionally have required human intellect. Concepts such as knowledge-based systems, inductive learning, fuzzy logic, genetic algorithms, and artificial neural networks are the foundational methods in this area (Pham & Pham, 1999). Engineering, automation, banking, healthcare, and the military are just a few fields that take advantage of these methods.

In complex problem-solving processes where traditional methods are limited, AI-based systems provide significant advantages by providing more flexible, learnable and adaptable solutions. For this reason, AI has become an indispensable technology that offers high efficiency in practical applications rather than being only a theoretical field of study. Mainly thanks to features such as symbolic reasoning and explainability, AI systems are used to strengthen decisions, support mechanisms and increase the transparency of processes.

In addition, AI provides significant contributions in processes such as modelling, analysis, prediction and control of complex systems. Thanks to these features, it solves current problems and plays a critical role in strategic planning for the future (Mellit & Kalogirou, 2008). This multifaceted nature of AI has made it a strategic technology both in the academic world and in industry.

AI can be defined as a technology that focuses on imitating human cognitive abilities and tries to model logical decision-making processes (Jiang et al., 2017). Unlike algorithms that operate only within the framework of specific rules, AI systems can flexibly adapt to various situations, make sense by analyzing data, and learn from past experiences (Seetharam et al., 2019). In this respect, AI offers the potential to make effective decisions even in dynamic and unpredictable environmental conditions.

Today, although the widespread use of computer technologies in many fields sometimes creates the impression that it overshadows the importance of AI the concept of AI is gaining more and more importance every day (Roads, 1985). While the rapid development of AI has the potential to transform social life, it has also brought along some ethical and philosophical debates. In particular, the idea that AI may threaten individual freedoms by reaching a point that can exceed human intelligence has led to various concerns among scientists. However, it is undeniable that if this technology is developed correctly and based on ethical foundations, it can provide significant benefits for individuals and societies (Hamet & Tremblay, 2017).

AI significantly contributes to many challenges such as managing complex decision-making processes, overcoming the lack of expertise, separating meaningful data among the masses of information and system integration. Thanks to these features, it is increasingly used in the production sector and enables enterprises to transform their operational processes. Robot technologies, among the industrial applications of AI, stand out

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as systems that provide high speed, efficiency and continuity in production lines. Robots can perform dangerous operations safely by stepping into areas where the workforce is insufficient or risky. This offers significant advantages in reducing occupational accidents, increasing production safety and protecting human health.

Although implementing AI-based systems in the manufacturing industry requires a high level of capital investment, the return on investment and operational efficiency it provides in the long term are at a level to justify this investment (Buchmeister et al., 2019). Therefore, the integration of AI technologies into production processes should be considered not only as a technological transformation but also as a strategic competitive advantage.

By increasing the integration of production and information communication technologies, AI makes information processing, communication and control processes more efficient and thus paves the way for higher value-added production. AI technologies play an essential role in functions such as sensing environmental conditions of production systems, adapting to external demands and transitioning to smart production models. It also contributes to defining process knowledge and developing new-generation production models such as extended cooperation (Wan et al., 2020).

The primary purpose of AI is to solve the problems that human intelligence can solve through computer systems. In this context, expert systems, one of the sub-branches of AI, offer decision support systems at an equivalent level to human experts by transferring specialist knowledge and experience in a specific field to the computer environment (Pirim, 2006).

Machine learning (ML), one of the main components of AI, uses statistical and algorithmic methods to detect hidden patterns in data. Thanks to these methods, systems can make predictions for the future by learning from past data. ML is a method that makes AI effective because it enables computer systems to learn independently and perform tasks such as classification and prediction (Johnson et al., 2018).

Deep learning (DL), a more advanced sub-discipline of ML, performs data processing similar to the working principles of neurons in the human brain using multi-layered artificial neural networks. Deep learning automatically learns distinctive features about a particular subject and produces results with high accuracy rates thanks to its complex prediction capabilities (Hosny et al., 2018). With these features, DL is increasingly used in complex tasks such as image recognition, natural language processing, voice analysis, and so on (Krittanawong et al., 2017; Shimizu & Nakayama, 2020).

The ultimate goal of AI systems is not only to make machines think like humans but also to develop systems that can make faster, accurate and consistent decisions by going beyond human cognitive capacity. The systems developed for this purpose are designed to have the capacity to collect and process information independently from the environment and to make decisions based on this information.

Nowadays, AI is not only limited to decision support systems; it is used to increase performance in many areas, from production to management in workplaces. In this context, various computer-based systems and applications such as machine learning, soft computing techniques, fuzzy logic systems, intelligent robots, and virtual and augmented reality represent the expanding domain of AI (Pereira et al., 2021).

2.Smart Production Systems

Smart manufacturing is a next-generation manufacturing approach that aims to improve systems and enhance strategic decision-making processes to increase flexibility and adaptability as a result of modern manufacturing technologies. This model enables the collection of big data from multiple data sources through cyber-physical systems and the processing of these data with advanced analytical techniques to produce high-value-added outputs (Cheng et al., 2021). Smart manufacturing aims to increase not only productivity but also the sensitivity of production processes and the ability to respond to environmental conditions.

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The integration of several technologies, including the Internet of Things (IoT), automation and robots, big data analytics, AI, cloud computing, and so on, shapes smart manufacturing systems in this environment. According to Thoben et al. (2017), these technologies form the foundation for a data-driven and interconnected supply network to become a reality. Therefore, all parties involved in the supply chain, as well as the machines themselves, can benefit from a continuous flow of information for the management of production processes.

Smart factories stand out as the physical counterpart of these systems, offering flexible and adaptable production processes under dynamic, complex and variable conditions, and providing effective solutions to the challenges faced in production. Such factories are equipped with automation systems that provide optimization to reduce unnecessary labor and resource waste. At the same time, a sustainable and agile production infrastructure is created through the integration of software, hardware and mechanical components (Hozdic, 2015). Smart manufacturing is not only a technical transformation but also an organizationally dynamic structuring that focuses on the cooperation of stakeholders from different sectors.

The architecture of smart manufacturing systems is given in Figure 1.

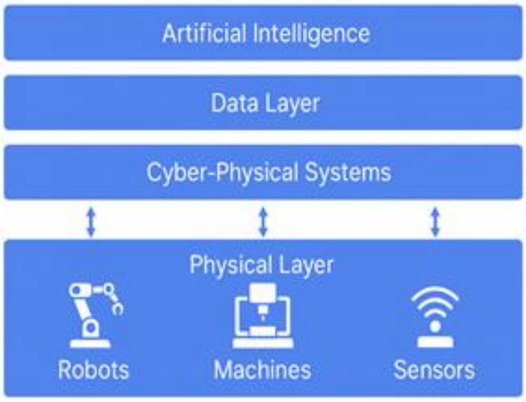

Figure 1. The Architecture of Smart Manufacturing Systems

The model illustrates a layered structure consisting of a physical layer (robots, machines, sensors), cyber-physical systems, data layer, and AI, reflecting the integrated nature of modern manufacturing under Industry 4.0. The architecture of smart production systems can be visualized as a multilayered structure that integrates physical components (robots, machines, sensors) with cyber-physical systems, data management technologies, and artificial intelligence. As shown in Figure X, these layers interact dynamically: the physical layer generates real-time data through machines and sensors, which is processed by cyber-physical systems and the data layer to support decision-making at the AI level. This structure facilitates real-time optimization, predictive maintenance, and adaptive manufacturing workflows (Choi et al., 2015; Hozdić, 2015; Waibel et al., 2017).

Cloud computing, the IoT, big data, and AI are just a few examples of revolutionary technologies that have arisen as a result of the fast progress in ICT. The concept of Industry 4.0 is based on the integration of these technologies into the manufacturing sector. They create a bridge between the physical and virtual worlds through cyber-physical systems (Zheng et al., 2018). Smarter, more responsive, and more efficient production processes are made possible by the growth of cyber-physical systems.

Smart manufacturing systems are defined by their flexible structure, efficiency in resource utilization, ergonomic design and ability to integrate customers and business partners into the value-creation process (Waibel et al., 2017). These systems represent an important paradigm shift in the manufacturing sector, especially by creating fully integrated and collaborative production networks that can respond instantly to variable demand conditions and individualized customer needs (Pascual et al., 2020; Ulusoy and Civek, 2020).

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Smart manufacturing systems are production models equipped with advanced technologies that offer multidimensional solutions to increase efficiency, quality and sustainability in production processes. These systems include many components such as instrumentation systems, condition monitoring systems, production execution systems and process control systems (Kannaraya et al., 2019). The main goal of smart manufacturing systems is to reduce costs and environmental impacts while maintaining production quality at higher levels of safety and productivity.

These systems continuously improve by monitoring processes, making operations more flexible, lean, agile and responsive. Production becomes more profitable, safe and sustainable by reducing waste, monitoring downtime, efficient use of energy resources, and transparent data management (Kaushal et al., 2019).

The three main objectives of smart manufacturing systems can be summarized as follows: plant-wide optimization, sustainable production and agile supply chains (Thoben et al., 2017). The ultimate goal of these systems is to eliminate defective products by adopting the zero-defect principle in the products delivered to customers. All inspection processes are carried out by automated machines; thus, defective products are detected at an early stage, taken out of the system and made reprocess able (Sarkar et al., 2019).

Unlike conventional manufacturing systems, intelligent manufacturing systems are capable of producing complex and customized products with high accuracy. This situation breaks the traditional perception that the production speed should be constant and enables a dynamic and customized production approach.

Digitalization will play a pivotal role in the next industrial revolution that the world is heading towards. Smart production systems are the backbone of this change. The IoT, big data, cloud computing, machine learning, additive manufacturing, computer numerical control (CNC) machines, and industrial robots are some of the information and operation technologies that constitute the basis of these systems (Choi et al., 2018). The success of smart manufacturing relies on enterprises tailoring and integrating these technologies to their unique production environments.

However, there are also various challenges in the process of transition to smart production systems. The first of these challenges is that employees do not have sufficient information technology infrastructure. In order for smart production systems to work effectively, the digital competences of all personnel need to be developed. Therefore, on-the-job training is more important than ever in terms of adopting new technologies and increasing usage skills (Waibel et al., 2017).

Another important challenge is the high initial investment costs. Small and medium-sized enterprises (SMEs) in particular may experience limitations in accessing the financial resources required for the transition to smart manufacturing systems. In some cases, the fact that these investments do not provide a direct return in the short or medium term may cause indecision.

Finally, information security is one of the main obstacles to smart manufacturing systems. The digitalization of production processes and the transition to cloud-based structures can make sensitive data vulnerable to external threats. Companies continue to hesitate to store production data in third-party systems, which necessitates the development of advanced cybersecurity solutions to ensure data security (Waibel et al., 2017).

3. Industrial Robots

3.1. Robot Concept

The concept of "robot" originates from the Czech word robota, which means "tireless work" or "drudgery" (Engelberger, 1980; Pires, 2007). Today, robots are defined as systems that can perform their tasks intelligently based on the principles of safety, flexibility, versatility and cooperation in many sectors, especially in production (Bahrin et al., 2016).

Robots are widely used to undertake repetitive, tedious and dangerous tasks and to perform physical actions such as carrying, holding and assembling heavy or bulky components. In parallel with technological developments, robots have become more flexible, collaborative and autonomous, thus expanding the range of

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services they offer. Modern robots are designed to be able to interact with each other and work safely in the same environment as humans. In addition, thanks to the integration of technologies such as AI and machine learning, robots have started to reach the capacity to learn complex tasks and perform these tasks like humans (Chuah, 2021).

In the context of Industry 4.0, robots have become one of the key components of autonomous production systems. This new industrial paradigm envisages that robots will not only be machines that perform pre-programmed tasks but also transform into interoperable learning systems that can adapt to environmental conditions. Modern robots can now operate safely in the same environment as humans without isolating their workspaces and thus provide more efficient solutions in production environments, both economically and operationally (Bahrin et al., 2016).

In the smart factories of the future, robots are expected to become lower-cost, more autonomous and collaborative systems with a wider range of functionality. These robots will be able to interact directly not only with machines but also with humans; they will take an active role in agile and personalized production processes thanks to their learning structures.

3.2. Industrial Robots

In recent years, the rapid development of smart technologies has enabled the deepening of automation in production processes and the optimization of various workflows both inside and outside production lines. In particular, the industry 4.0 approach has led to revolutionary transformations in manufacturing by promoting the use of automated robots and smart machines that make production systems data-driven and flexible (Krishnan & Mendoza Santos, 2021).

Industrial robots are defined as programmable manipulators and are integrated into the production process by automatically repeating a specific process cycle (Todd, 1986). These robots have been used in mass-production processes for many years and are preferred to increase production speed, eliminate human-induced delays, ensure production safety and increase operational efficiency (Sabzehmeidani, 2021). Robot-assisted production also reduces product costs and increases competitiveness by shortening delivery times.

The development of industrial robots is based on a complex technology infrastructure consisting of a wide variety of disciplines. In this context, especially the fields of robot control and motion control constitute the basic building blocks of industrial robotics. Advances in these areas contribute directly to the continuous improvement of robot performance and the reduction of production costs (Brogårdh, 2007).

Industrial robots are used in many demanding production tasks, such as transporting heavy loads, handling hazardous materials, and assembly operations requiring high precision (Todd, 1986). In these aspects, they both contribute to occupational health and safety and make it possible to carry out physical tasks that exceed the limits of manpower more safely.

Recently developed robots stand out not only with their high operational capacity but also with their flexibility, autonomy and cooperation capabilities. These new-generation robots, which can operate in the same workspace as humans, share tasks and interact safely, offer significant productivity potential by strengthening human-machine synergy in production environments (Evjemo et al., 2020).

The industry 4.0 paradigm expects robotics not only to be task-oriented but also to be intelligent systems that can perceive their environment, make decisions according to the situation, cooperate safely with humans and learn new tasks. In particular, assembly tasks are one of the important application areas where these competencies are tested, and they are high-precision operations that robots perform autonomously or in collaboration with human operators (Roveda et al., 2021).

The adoption of robots in production processes provides a comparative advantage, especially in automatable tasks, and significantly increases the output level of firms. Moreover, since robots can substitute human labor, they also contribute to reducing the share of labour costs in production (Koch et al., 2021).

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3.3. Autonomous Robots

In line with the digital transformation vision offered by Industry 4.0, robots are becoming increasingly autonomous, flexible and collaborative systems. This transformation encourages the development of robots as intelligent systems that can interact with each other and with humans, work safely side by side in the same production environment, and perform tasks by learning from humans (Vaidya et al., 2018).

Autonomous robots can carry out production activities, especially in areas where access to human employees is limited or risky; they complete tasks with high precision and intelligence within the specified time, bringing safety, flexibility, versatility and efficiency to production systems. Thanks to their advanced AI algorithms, these robots can perceive their environment, make decisions and maximize production performance by adapting to various conditions.

Developments in AI technologies, especially deep learning, machine learning, and computing hardware such as graphics processing units (GPUs) and neural processing units (NPUs), have significantly increased the cognitive capacity of robots (Liu et al., 2022). This trend has made it possible for robots to be designed as human-centered, flexible and self-learning systems, going beyond merely performing predefined tasks.

Nowadays, robotic systems allow even non-robotic experts to safely interact with these systems and teach different tasks thanks to user-friendly interfaces. Such approaches enable robots to be easily integrated into different production lines and flexibly reconfigured in different tasks (Indri et al., 2018).

Industrial robots are actively used in many areas, such as material handling, assembly (especially in the automotive and electronics sectors), and additive manufacturing (such as 3D printing and food production). In today's manufacturing world, increasing demands for high levels of customization, small batch production and short planning times have led to the need for robots to be versatile, reprogrammable and highly adaptable.

One of the key technologies for robots to fully adapt to smart manufacturing processes is visual perception systems. Especially thanks to 3D computer vision, robots can detect and recognize objects and estimate their position and position in three-dimensional space. In this way, they can perform more complex tasks in the production environment with high precision (Zhang et al., 2022).

Autonomous robots are being developed to have the ability to make decisions and take action like humans. Using these robots in enterprises has reduced the error rates in production processes, significantly reduced the time and cost allocated for process control and thus provided a competitive advantage to companies (Bolatan, 2020).

4.Dark Factories

Dark factories, one of the most advanced applications of smart production systems, are defined as facilities where production processes are fully automated and operate without the need for human intervention. In such factories, an ecosystem is established where all objects are interconnected and supported by the IoT infrastructure. Transparency, simultaneous traceability, preventive maintenance, flexible adaptation and optimum efficiency are adopted as basic principles in the production process (Şekelli & Bakan, 2018).

The "lights-out technology" used in dark factories is one of the main symbols of this production approach. This technology allows production to continue throughout the night without the need for human presence. This makes it possible to focus on more complex processes during the day while saving energy and significantly reducing labor costs. In this respect, the system has become an accessible solution not only for large-scale manufacturers but also for SMEs with appropriate integration strategies (Lee, 2018). Dark Factory Workflow is given in Figure 2.

The diagram illustrates the fully automated production flow in a dark factory environment, including stages from material supply to shipment with minimal or no human intervention. As illustrated in Figure 2, the workflow in a dark factory typically includes six core stages: material supply, automated production, automated inspection, automated storage and retrieval, automated packaging, and automated shipment. Each

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of these steps is executed without human intervention, facilitated by advanced robotic systems, AI-based decision-making algorithms, and real-time data integration via IoT infrastructures. This uninterrupted, data-driven workflow significantly enhances production efficiency, reduces labor dependency, and minimizes operational risks (Şekelli & Bakan, 2018; Lee, 2018; Bolatan, 2020).

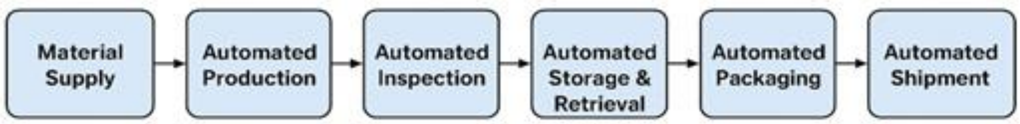

Figure 2. Dark Factory Workflow

Another important advantage of dark factories is their contribution to occupational health and safety. In hazardous work environments such as high temperature, toxic gas, heavy load handling, oven management, paint line operations or carbon fibre cutting, the use of robotic systems eliminates the risks that workers may be exposed to and safe production processes are created. This situation also improves the quality control process by preventing human-induced errors to a great extent and reduces the need for re-processing faulty production (Bolatan, 2020).

Dark factories offer not only technical advantages but also strategic and sustainable competitive advantages. Coordination is ensured thanks to simultaneous access to information by manufacturers and suppliers, time costs are reduced by accelerating processes, quality is increased with automation and flexible digital production conditions are created. All these factors are the main reasons for the increasing tendency towards the dark factory model in the digitalizing industrial structure (Şekelli & Bakan, 2018).

Although dark factories offer many advantages, they also bring several limitations and practical concerns. Firstly, this production model is not suitable for every sector. Especially in areas such as the food industry, where cold, humid and hygienic conditions are critical, automation is limited in both production and packaging stages. Similarly, production environments that require high precision and quality or complex assembly processes in the aircraft industry have difficulty adapting to the dark factory model due to technical risks and complexity (Lee, 2018).

Another important issue related to this production model is equipment reliability. In systems that operate without human intervention, failure to recognize the problem in the event of a malfunction can lead to chain disruptions. However, in traditional production environments, an operator can instantly observe the problem in the machine and correct the process by manually intervening. In autonomous systems, such problems can accumulate and cause serious interruptions in production lines if monitoring and maintenance processes are insufficient.

This transformation also has significant effects on the employment structure. Dark factories reduce the need for unskilled labor and increase the demand for highly educated and qualified personnel. Now, there is a need for expert employees who not only supervise the operation of machines but also perform software installations, manage automation systems, analyze production processes and make emergency interventions (Akben & Avşar, 2018).

While dark factories offer operational efficiency and cost reduction, they also raise ethical and social concerns. One of the primary dilemmas is job displacement, particularly for low-skilled workers whose roles are entirely automated. Without adequate re-skilling initiatives and inclusive education policies, this transformation may deepen the digital divide between those with access to digital competencies and those without. Additionally, the environmental impact of energy-intensive automation, e-waste, and increased carbon footprint from continuous operations must be critically assessed. Ensuring that technological progress

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in manufacturing aligns with social justice and sustainability goals is essential for long-term acceptance and ethical legitimacy (Winfield & Jirotka, 2018; Pereira et al., 2023).

At this point, it is of great importance for states to prioritize education policies in order to reduce labor mismatches and unemployment risks that may be encountered in the future. The training of competent human resources will ensure the balanced development of the social structure along with the technological transformation.

However, one of the alternative solutions suggested is the tax application for robots. If businesses have to pay taxes at certain rates for the robots they use, they may prefer human labor in some tasks by providing balance in cost calculations. This is considered as a policy tool that can reduce the risk of social unemployment (Yılmaz, 2021). However, the long-term and sustainable solution is to encourage human resource transformation in production processes and prioritize education investments to increase the qualified labor force.

5.Conclusions And Recommendations

In this study, concepts such as intelligent production systems, industrial robots and dark factories, which are one of the main components of Industry 4.0, are discussed in detail. Today, the manufacturing industry is going through an evolutionary process that necessitates digital transformation to achieve multidimensional goals such as responding quickly to increasing customer demands, providing high quality at low cost, ensuring sustainable production and gaining global competitive advantage.

One of the most fundamental requirements facing the manufacturing industry today is the production of higher-quality products with shorter lead times. In this context, advances in internet-based information technologies and communication enable distributed enterprises worldwide to use complex sets of systems consisting of software and hardware in an integrated manner for rapid product development and product lifecycle management (Ram & Lawrence, 2019). With this digitalization process, today's complex business structures require integrated, automated and intelligent production systems. Indeed, smart manufacturing refers to the intensive and widespread application of networked information-based technologies, especially in production and supply chain (Kaya ve Yıldız,2024) processes (Davis et al., 2012).

The Smart Manufacturing Systems approach offers multifaceted benefits to businesses, providing efficiency, flexibility and customization advantages at all levels. Companies can produce customer-specific, high-tech and individualized parts at mass production costs; production lines can be adjusted in a short time and processes can be monitored and controlled beyond geographical borders. Robots, one of the most important components of these systems, contribute to the creation of ergonomic workstations, making human-machine cooperation safer and more flexible (Waibel et al., 2017).

Robot technology is not only limited to industrial areas but has become a field that arouses interest and admiration at both technical and social levels, as it has a wide range of uses from the home environment to space. The focus of this study is on robots used in industrial production processes and developed to replace humans. These robots are involved in production processes like mechatronic colleagues and perform tasks with high accuracy (Pires, 2007).

Industrial robot technology is evolving towards more and more intelligence-oriented systems. Technological breakthroughs and the development of the manufacturing industry have made these systems not only desirable but also a necessary component (Ruishu et al., 2018). The new generation of intelligent robots can not only understand the tasks they need to perform but also analyze human actions and intentions and engage in predictive behavior. Thanks to the developing communication infrastructure between robots, their general perception capabilities are also strengthened (Ruishu et al., 2018).

Another advantage of this transformation is the capacity to offer employees more flexible working environments. The ability to monitor and manage production processes from anywhere in the world makes it

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possible to better tailor work to the individual life circumstances of employees, thus making significant progress in work-family balance (Waibel et al., 2017).

The new production paradigm shaped with Industry 4.0 emphasizes a structure based on smart and flexible systems where connectivity between humans, machines, software, robots and devices is the basic principle. Technologies such as the IoT, robotics, flexible production systems, virtual and augmented reality applications, big data analytics and smart maintenance are integrated in a single digital environment and form the basis of fast, economical and reliable production systems (Reji et al., 2019).

As industrial robots become more autonomous and capable of decision-making, ethical questions regarding responsibility, transparency, and safety arise. One major concern is accountability—when robots make errors or cause harm, determining who is responsible becomes complex. Furthermore, as robots increasingly take on decision-making roles, ensuring that these decisions align with ethical principles and human values is essential. Occupational safety is also central, especially in human-robot collaborative environments where physical interaction occurs. It is critical to ensure that robotic systems are transparent, predictable, and designed with fail-safe mechanisms. Embedding ethical frameworks into robotic development is no longer optional but a necessary condition for sustainable industrial transformation.

In parallel with these developments, the need for multi-skilled and versatile human resources has come to the fore instead of unskilled labor in the production industry. The required employee profile now consists of individuals who can master multiple skills, different technologies and production processes at the same time, and have flexible information infrastructure. It is clearly seen that in dark factories, one of the main components of Industry 4.0, there is only room for competent labor, while unskilled labor is dysfunctional in these systems (Yılmaz, 2021). In this context, the need for technical specializations such as technicians, technicians and engineers is increasing; therefore, the quality of human resources has become a strategic element for the success of digital production systems. Although these technologies offer great benefits to the production sector, they also bring some technical, economic and sociological challenges in terms of applicability (Dilek, 2010). Especially in cold, humid or high-precision production environments, the effectiveness of dark factories is limited. In addition, the absence of people in the field in cases such as machine failures may cause the system to stop or the failure to grow with chain effects. However, high investment costs constitute a significant barrier, especially for small and medium-sized enterprises. Such transformations require not only technological infrastructure but also a cultural and structural adaptation process. One of the most critical points is the change in the labor force profile. The need for unskilled labor is gradually decreasing, while the demand for competent human resources with technical knowledge, multidisciplinary thinking and the ability to manage the digital aspect of production processes is increasing. Strategic investments should be made in vocational and technical education in order to train the labor force with the skills required by Industry 4.0, and STEM (Science, Technology, Engineering and Mathematics) focused curricula should be expanded. State policies should prioritize the goal of creating "skilled human resources". Special incentives, tax breaks and technology transformation funds should be provided to small and medium-sized enterprises to offset the high investment costs of transitioning to dark factories. In order for all digital production systems to operate securely, data protection measures should be increased; security of cloud systems, AI-based threat detection and resilience strategies against cyber-attacks should be developed. Alternative models should be developed against the risks of unemployment that may arise due to automation, and social stabilizing mechanisms such as a taxation system for the use of robots should be open to discussion. Robots should aim not only to replace human labor but also to cooperate with it. In this context, ergonomic workstations, augmented reality-supported systems and hybrid solutions for occupational health and safety should be encouraged.

Ethical Considerations of the Study

It is declared that the study was designed to realistically and ethically meet the needs, and that integrity was maintained in obtaining data, concluding the study, and publishing the results. Ethical committee approval was not required for this research. No research requiring ethics committee approval was conducted in this study.

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Informed Consent

There was no need to obtain informed consent from individuals, as the study did not involve any procedures or interventions on human participants.

Author Contributions

Idea/Concept: F.S.A.; Design: F.S.A.; Supervision/Consultancy: F.S.A.; Resources: F.S.A.; Data Collection and/or Processing: F.S.A.; Analysis and/or Interpretation: F.S.A.; Literature Review: F.S.A.; Writing: F.S.A., F.S.A.; Critical Review: F.S.A.

Conflict of Interest Statement

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Declarations

This study has not been presented at any congress.

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