Redefining Human-Machine Collaboration: Industry 5.0 to Improve Safety and Efficiency

Francisco Antonio Lloret Abrisqueta, Antonio Guerrero Gonzalez, and Roberto Zapata Martinez

***Abstract*—This study presents an innovative implementation of Industry 5.0 principles in a window production line, integrating advanced robotics and artificial intelligence technologies to improve operational efficiency and worker well-being. A robotic cell was designed to automate the handling of heavy components in the final production stage, resulting in a 35% reduction in cycle times and a significant decrease in ergonomic risks. Additionally, an interactive voice assistant based on generative AI was implemented, allowing operators to access system data and technical information in real-time through cognitive interaction. The results show a substantial improvement in job satisfaction, with a 278% increase in the perception of occupational health. This approach not only optimizes productivity but also redefines workers' roles, aligning with the human-centered vision of Industry 5.0. The study demonstrates how the integration of advanced technologies can create safer, more efficient, and adaptable work environments in modern manufacturing.**

Link to graphical and video abstracts, and to code: https://latamt.ieeer9.org/index.php/transactions/article/view/9412

***Index Terms*—Advanced robotics, Generative AI, Industry 5.0, Occupational Health**

I. Introduction

THE manufacturing industry is at a turning point, facing increasingly complex challenges that demand innovative solutions. The need to improve efficiency, reduce costs, and minimize risks has become particularly pressing in sectors such as window manufacturing, where manual handling and classification of heavy components not only affect productivity but also expose workers to significant musculoskeletal injuries [1]. The growing demand for flexible, sustainable, and human-centered solutions underscores the importance of adopting cutting-edge technologies. In response to these challenges, Industry 5.0 emerges as a paradigm that seeks to integrate Industry 4.0 technologies [2] with a closer human-machine collaboration, aiming to create safer and more efficient work environments centered on employee well-being [3], [4]. However, the transition to this new industrial model is not without obstacles. One of the main challenges lies in the dependence on proprietary systems, which limit flexibility and hinder the integration of new technologies into existing production lines [5].

To address this, we propose an interactive voice assistant based on generative artificial intelligence, which will enhance operations by enabling real-time interaction with operational data and facilitating predictive maintenance without halting production [6]. Additionally, a robotic assistant will be incorporated to minimize physical strain on operators. This assistant will implement protocols such as MQTT and OPC UA, allowing seamless communication between systems [7], [8]. This approach not only increases operational efficiency but also redefines the role of workers, aligning with the principles of Industry 5.0 [9], [10].

The main objectives of this study are:

1) To explore the integration of robotics and artificial intelligence in optimizing industrial production, with a focus on window manufacturing.
2) To evaluate the impact of these technologies on occupational health and worker satisfaction.
3) To propose an implementation model that exemplifies the principles of Industry 5.0, prioritizing human-machine collaboration and employee well-being.
4) To analyze the implications of this technological transformation on job roles and the skills required in modern manufacturing.

This paper is structured as follows: Section *II. State of the Art* provides a focused review of the state of the art in industrial automation and Industry 5.0 technologies, highlighting existing methodologies and gaps. Section *III. Materials and Methods* details the materials and methods used in implementing the proposed solution. Section *IV. Results* presents the results, including improvements in production efficiency and working conditions. Finally, Section *V. Conclusion* discusses the broader implications of our findings and draws conclusions on the future of Industry 5.0 in manufacturing.

II. State of the Art

The manufacturing sector has witnessed significant advancements in automation, redefining industrial production processes. The transformation of the production line through advanced automation reflects the latest progress towards Industry 4.0. However, when these advancements align with close collaboration with humans, the transition to Industry 5.0 takes place [3].

A key aspect of this improvement is the incorporation of an interactive voice assistant based on generative artificial intelligence (Generative AI), allowing operators to access system data and technical manuals in real-time [11]–[14] , enabling interaction with this data in a graphical format or through

The associate editor coordinating the review of this manuscript and approving it for publication was Javier Moreno-Valenzuela (*Corresponding author: Francisco Antonio Lloret Abrisqueta*).

Francisco Antonio Lloret Abrisqueta, A. G. González, and R. Z. Martínez are affiliated with the Technical University of Cartagena, Cartagena, Spain (e-mails: francisco.lloret@upct.es, antonio.guerrero@upct.es, and roberto.zapata@upct.es).

speech recognition and synthesis [15]. This technology not only facilitates problem-solving and predictive maintenance but also optimizes efficiency by allowing workers to interact directly with the system without stopping production [16]–[19]. The application of natural language processing (NLP) in industrial environments represents a significant leap in human-machine interaction, allowing intuitive control and real-time adaptability [11], [12], [20]. To achieve this, open standards such as OPC UA and MQTT have been adopted, enabling seamless and secure integration between various plant components [21]–[23]. These protocols facilitate connectivity between heterogeneous systems and devices, ensuring greater flexibility and scalability in the production line [21], [24].

Industrial robots have emerged as a fundamental technology, providing not only precision in handling tasks but also consistency and repeatability, minimizing human error [25], [26]. By replacing manual handling with robots, the risk of errors is drastically reduced, and plant efficiency is improved [25], [27], [28]. Therefore, improving the final stage of production through robot implementation will minimize the risk of work-related injuries caused by repetitive handling [27], [29], [30]. This type of automation addresses a recurring issue in manufacturing: physical overload and ergonomic risks for workers performing repetitive manual tasks [7], [31], [32].

However, Industry 5.0 does not stop here, as other technologies further enhance these developments. For instance, the integration of digital twins improves this ecosystem by bridging the physical and virtual realms for monitoring and optimization [33], [34]. Cloud computing facilitates access to and processing of large volumes of data in real-time [35], [36]. Leveraging the power of the cloud enhances system capabilities [37], [38]. Cloud computing enables the execution of data-intensive tasks without overloading local systems, increasing system efficiency and responsiveness [39], [40]. Despite these advancements, challenges such as cybersecurity and sustainability remain critical. Increased system connectivity demands robust security measures to protect against potential cyber threats [22], [41]. Similarly, the emphasis on sustainability requires evaluating technological solutions based on their environmental impact, including energy efficiency and carbon footprint reduction [42], [43].

The implementation of these technologies in the plant aligns with Industry 5.0, promoting closer collaboration between humans and machines [44], [45]. This evolution not only enhances the plant but also redefines the role of operators, freeing them from repetitive tasks and allowing them to focus on higher-value-added activities [46], [47]. The Industry 5.0 approach also emphasizes improving working conditions, addressing both ergonomics and worker safety [31], [41].

III. Materials and Methods

A. System Description

The development plant, in this case, a Schirmer machine, plays a fundamental role in the window production line, being responsible for the initial cutting and machining of aluminum and PVC profiles. Designed to accommodate a variety of profile sizes and configurations, the plant utilizes CNC technology to perform precision cuts and specific machining operations such as drilling and slotting, meeting the required specifications for each production batch.

The plant consists of different stages (Fig. 1) to achieve the final product. The first stage is the manual feeding of the profiles through *input 1*, followed by processing as indicated in the figure, adding reinforcements for manufacturing from *input 2*. These reinforcements, after passing through the conveyor, are joined and drilled to obtain prepared profiles for the next stage (*Output*). The transition between stages involves manually loading a transport cart.

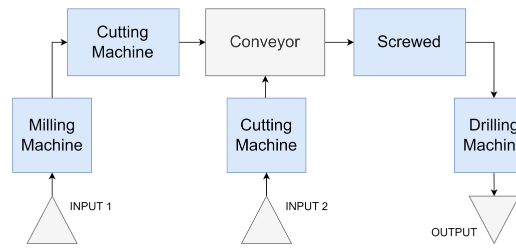

Fig. 1. Layout of the different parts of the plant.

B. Robot Implementation

The implementation of the robot in the production line focused on replacing heavy and repetitive manual handling tasks related to cart loading, improving both efficiency and ergonomics [29]. The robot was specifically selected for its advanced capabilities in terms of payload and motion precision. With a payload capacity of up to 235 kg and an operational reach of 3.2 meters, this model offers a repeatability of ±0.07 mm [48], essential characteristics for handling large volumes and ensuring the precision required for window component manipulation.

Fig. 2. Industrial robot integrated for handling heavy components.

The first step was designing and simulating the robotic cell in a virtual environment. This enabled the generation of pick-and-place points for the components, optimizing trajectories and ensuring efficiency in the work cycle. Subsequently, the programmed trajectories and points from the simulation were transferred to the robot controller's RAPID code. The gripper, manufactured by Zimmer, was selected for its adaptability to the specific components of the production line. Real-time communication tests were conducted between the robot and the control system. These tests included synchronization with the gripper's magnetic sensors, monitoring of open/close states, and verification of digital signals, ensuring that each robot movement met operational specifications. The system was verified through initial movement tests on all six robot axes to ensure optimal functionality in handling tasks.

C. Interactive Voice Assistant

The virtual assistant is integrated into the production line using the existing network infrastructure, expanded to support the necessary communication demands [14]. It is managed through a graphical user interface (GUI) featuring a chat-style dialog box that allows operators to communicate with the assistant. Additionally, it incorporates voice recognition and synthesis capabilities, essential for a completely hands-free interaction in the industrial environment—ideal for scenarios where visual attention must remain focused on operations. The AI-based voice assistant structure for the production plant is organized into modules designed to import necessary functions from a single central program. This modular architecture enables system scalability and facilitates maintenance (Fig. 3).

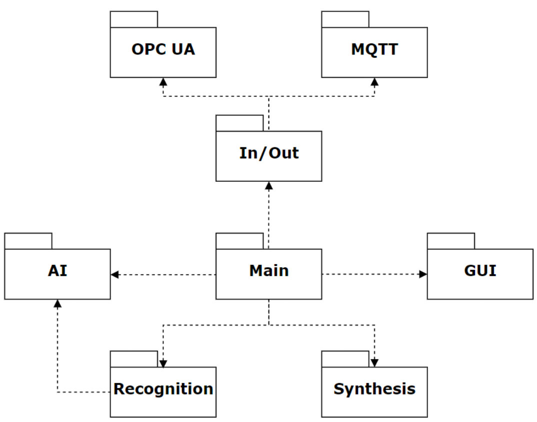

Fig. 3. UML diagram of the voice assistant's modular architecture.

The system architecture is composed of the following modules:

- **Main Module** `main.py`: Serves as the central controller integrating voice recognition, interaction with ChatGPT, and speech synthesis.
- **Recognition Module** `reconocimiento.py`: Implements voice recognition using Google Speech Recognition.
- **Synthesis Module** `sintesis.py`: Converts text to speech using Google Text-to-Speech (GTTS) or ChatGPT's speech synthesis service.
- **AI Module** `chatGPT.py`: Manages connection and communication with ChatGPT. It initializes the AI assistant, processes user queries, and handles file uploads.
- **GUI Module** `IG.py`: Manages the graphical user interface, displaying the chat dialog and processing user inputs.
- **In/Out Module** `EyS.py`: Modifies program operation by selecting real-time data sources.
- **MQTT Module** `globalC.py`: Provides MQTT functionality to the assistant, subscribing to topics, extracting relevant data, and handling real-time communication between devices.
- **OPC UA Module** `localC.py`: Provides OPC UA functionality to the assistant, facilitating the retrieval of operational data and ensuring interoperability with industrial control systems in real-time.
- **Configuration:**
  - `variablesG.py`: Defines global variables and shared events across the system to ensure consistency.
  - `json_Hilos.py`: Manages configuration and data storage using JSON files.

To ensure accurate responses, the assistant leverages the OpenAI API, accessing advanced language models such as GPT-4. This large-scale multimodal model has excelled in various academic and professional evaluations, including the simulated bar exam, where it scored in the top 10% of human examinees [49]. Compared to previous models, this model better aligns with user instructions, improves factual accuracy, and reduces hallucinations, which is critical for a virtual assistant requiring reliability and adaptability. Additionally, the assistant benefits from a vector storage system, where operation manuals are stored through the creation of OpenAI assistants. Combined with real-time data reporting, this system allows storing, retrieving, and contextualizing information from manuals and plant-specific operational guides, providing quick access to technical documentation [50]. This is achieved through a system based on tokens, which are defined as the minimum units of text that allow artificial intelligence to break down and process the language to generate coherent responses. These tokens are then used for subsequent billing for the use of the assistant.

Although the supported machine can operate independently, the assistant enhances its functionality by addressing both plant-specific and general queries. Regarding response security, it is improved thanks to the system's reliance on operational data and real-time document retrieval, minimizing the risk of hallucinations. Additionally, to mitigate risks, the system employs activation words to prevent unintended operations.

IV. Results

A. Impact on Production

The implementation of the robotic cell has optimized production efficiency, achieving a 35% reduction in cycle time, decreasing from 15 to 9.5 seconds per operation. This automation has facilitated continuous operation and significantly reduced errors in the component classification process. Additionally, the incorporation of an interactive assistant has allowed a 25% reduction in waiting times, as workers can resolve minor issues without needing to call a specialized technician. In terms of job roles, the robotic cell has freed workers from repetitive and physically demanding tasks, allowing them to focus on higher-value activities. This not only optimizes workflow but also fosters effective collaboration between humans and technology, aligning with the principles of Industry 5.0 [51].

B. Interactive Voice Assistant

To evaluate the effectiveness of the assistant, an interaction test was conducted with plant operators, measuring the accuracy of its responses and its audio detection capability.

The evaluation of the voice assistant (Table I) shows high performance under optimal conditions, such as a neutral accent and low to medium noise levels, achieving up to 100% accuracy with fast response times. However, under conditions of fast or slow speech, or high noise levels, accuracy decreases and processing time increases. Interruptions and tone variations present the greatest challenges, significantly increasing response time. These results indicate that the assistant is effective. However, the increase in processing time is not solely due to the assistant but also to the limitations of the speech recognition system's processing capacity; this is observed when the same instruction under identical speech conditions yields different processing times.

TABLE I
ACCURACY EVALUATION OF THE VOICE ASSISTANT UNDER DIFFERENT CONDITIONS

Condition	**Accuracy (%)**	**Processing Time (s)**
Neutral Accent	98.6	1.031
	100.0	1.216
Fast Speech	88.2	0.935
	100.0	1.436
Normal Speech	98.6	1.399
	100.0	1.698
Slow Speech	88.6	0.936
	100.0	1.497
Low Background Noise	98.6	0.809
	100.0	1.458
Medium Background Noise	98.6	0.894
	100.0	1.668
High Background Noise	93.2	1.019
	97.6	1.704
Simple Instructions	98.6	0.869
	100	0.492
Complex Instructions	97.2	1.864
	97.4	2.404
Interruptions	93.6	1.648
Tone Variation	92.6	2.029

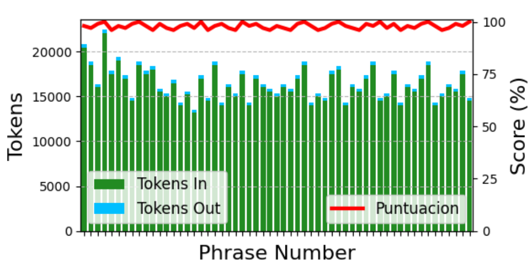

Fig. 4. AI assistant performance based on token usage and accuracy.

Fig. 4 shows the analysis of the assistant when processing each sentence, evaluating the number of Tokens In (input), Tokens Out (output), and the Response Score in terms of accuracy. The X-axis represents the number of analyzed sentences, while the left Y-axis shows the number of processed tokens, and the right Y-axis reflects the information retrieval score. Tokens In (green) remain relatively constant, indicating a stable volume of processed information due to the need to supply reports as Tokens In. Tokens Out (blue) vary more, suggesting that some queries require more extensive responses. The Score (red) remains high, close to 100%, indicating that the assistant maintains its accuracy without performance degradation. Overall, the system dynamically adapts the length of its responses according to the complexity of each sentence, while the stability in Tokens In suggests that the size of queries is relatively uniform, as the same reports are supplied for all messages.The results confirm that the AI assistant is a reliable, efficient, and context-aware solution, making it a key tool for addressing industrial challenges.

C. Improvement of Human Conditions

The implementation of a robotic cell for manufacturing tasks has shown a remarkable improvement in working conditions, mainly through a significant reduction in physical fatigue and musculoskeletal injuries. To assess the impact of automation in the work environment, a survey was conducted among the affected personnel, focusing on overall satisfaction and perceived improvements in occupational health after the implementation of the robotic cell. The survey included questions designed to measure various aspects of the impact of automation, such as overall satisfaction with the cell, perception of improvements in working conditions, and evaluation of occupational health before and after the change. Specific questions were also included on the reduction of musculoskeletal injuries and the decrease in physical fatigue. The responses were quantified on a scale from 1 to 10, where 1 represents the lowest level of satisfaction or improvement, and 10 the highest level. The results obtained are presented in Fig. 5:

- Satisfaction with the robotic cell: **8.96**
- Improvement in working conditions: **8.40**
- Occupational health before implementation: **2.44**
- Post-implementation health improvement: **9.22**
- Reduction of musculoskeletal injuries: **8.82**
- Reduction of physical fatigue: **7.06**
- Satisfaction with the virtual assistant: **9.22**
- Ratio of correctly generated responses: **7.62**
- Ease of use of the assistant: **7.34**

These results reflect a positive perception among employees towards automation, highlighting improvements in health and ergonomics in the work environment, as well as an increase in overall job satisfaction.

D. Discussion

The automation of the production line has demonstrated significant improvements in efficiency and ergonomics, achieving a 35% reduction in cycle times and decreasing operators' physical effort, reflected in a 278% improvement in occupational health perception. Additionally, the integration of an

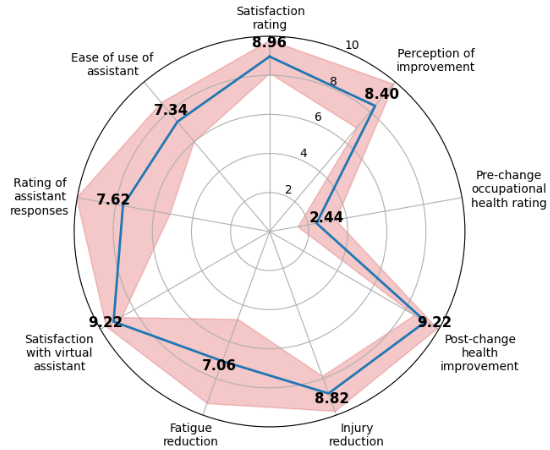

Fig. 5. Survey results on worker satisfaction and health improvements.

AI-based virtual assistant has optimized interaction with the production system, facilitating real-time access to information and improving process monitoring.

These results suggest that automation not only increases productivity but also has a positive impact on workers. The virtual assistant has shown an accuracy of 98.6% under optimal conditions, although in environments with high industrial noise, it dropped to 93.2%. The integration of open protocols (OPC UA and MQTT) has enabled a flexible and scalable infrastructure.

Despite the benefits, key challenges remain. The high input token consumption (15000-20000 per interaction) poses a challenge in terms of efficiency and operational costs. Additionally, the model's dependence on the cloud makes it vulnerable to network interruptions, which could affect its availability in industrial environments. To mitigate this, local models should be explored to allow for more autonomous operation, reduce latency, and improve data security without compromising the assistant's accuracy. However, this challenge is limited, as the assistant has an exclusively consultative role and does not directly intervene in plant operational control, thereby avoiding critical risks in production.

V. Conclusion

The implementation of a state-of-the-art robotic cell and a generative AI-based voice assistant in production line has proven to be an innovative solution that optimizes operational efficiency and revolutionizes working conditions, perfectly aligning with Industry 5.0 principles. The automation of repetitive and ergonomically challenging tasks has resulted in a 35% improvement in production efficiency, reducing cycle time from 15 to 9.5 seconds per operation [27], [52].

This synergistic integration of advanced AI in the production environment exemplifies the human-machine symbiosis proposed by Industry 5.0. The system architecture, based on open protocols such as OPC UA and MQTT, provides a robust, flexible, and highly scalable infrastructure. This technological choice not only ensures interoperability between various system components but also establishes a solid foundation for future iterations and adaptations, anticipating the continuous evolution of industrial technology [22].

The impact of this digital transformation on work roles has been profound and multifaceted. Operators, freed from monotonous and physically demanding tasks, have evolved toward higher value-added roles, focusing on process supervision, real-time data analysis, and strategic decision-making. This reconfiguration of responsibilities not only increases employee satisfaction and engagement but also optimizes the utilization of human capital in the plant, elevating the level of expertise and intellectual contribution in the production process [11].

The integrated implementation of the robotic cell and interactive voice assistant has generated a more efficient, safe, and adaptive work ecosystem. The significant reduction in cycle times, combined with substantial improvement in ergonomic conditions and the optimization of operational roles, demonstrates the transformative potential of cutting-edge technologies in modern manufacturing [35], [53].

Empirical results suggest that the strategic integration of advanced automation technologies and artificial intelligence in industrial environments can trigger exponential improvements in production efficiency and working conditions. Future research lines could explore the applicability and scalability of these technologies in various industrial sectors, as well as examine their longitudinal impact on key metrics such as productivity, job satisfaction, and operational sustainability. Additionally, it is recommended to investigate the potential implementation of Industry 5.0 principles in other critical phases of the production process, aiming to achieve a holistic and systemic transformation of the manufacturing value chain.

Acknowledgments

The content was translated from the original language into English through the implementation of the ChatGPT-4 artificial intelligence system, which was employed specifically for the purpose of performing this linguistic conversion.

References

[1] S. Kumar, "Theories of musculoskeletal injury causation," *Ergonomics*, vol. 44, no. 1, pp. 17–47, 01 2001. doi: 10.1080/00140130120716.

[2] H. Lasi, P. Fettke, H.-G. Kemper, T. Feld, and M. Hoffmann, "Industry 4.0," *Business & Information Systems Engineering*, vol. 6, no. 4, pp. 239–242, 08 2014. doi: 10.1007/s12599-014-0334-4. [Online]. Available: http://link.springer.com/10.1007/s12599-014-0334-4

[3] S. Nahavandi, "Industry 5.0—a human-centric solution," *Sustainability*, vol. 11, no. 16, p. 4371, 08 2019. doi: 10.3390/su11164371. [Online]. Available: https://www.mdpi.com/2071-1050/11/16/4371

[4] C. Turner and J. Oyekan, "Manufacturing in the age of human-centric and sustainable industry 5.0: Application to holonic, flexible, reconfigurable and smart manufacturing systems," *Sustainability*, vol. 15, no. 13, p. 10169, 06 2023. doi: 10.3390/su151310169. [Online]. Available: https://www.mdpi.com/2071-1050/15/13/10169

[5] J. Lee, B. Bagheri, and H.-A. Kao, "A cyber-physical systems architecture for industry 4.0-based manufacturing systems," *Manufacturing Letters*, vol. 3, pp. 18–23, 01 2015. doi: 10.1016/j.mfglet.2014.12.001. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S221384631400025X

[6] A. Ragmani, A. El Omri, N. Abghour, K. Moussaid, and M. Rida, "A performed load balancing algorithm for public cloud computing using ant colony optimization," in *2016 2nd International Conference on Cloud Computing Technologies and Applications (CloudTech)*. IEEE, 05 2016, pp. 221–228. doi: 10.1109/CloudTech.2016.7847703. [Online]. Available: http://ieeexplore.ieee.org/document/7847703/

[7] M. S. Forde, L. Punnett, and D. H. Wegman, "Prevalence of musculoskeletal disorders in union ironworkers," *Journal of Occupational and Environmental Hygiene*, vol. 2, no. 4, pp. 203–212, 04 2005. doi: 10.1080/15459620590929635 . [Online]. Available: http://www.tandfonline.com/doi/abs/10.1080/15459620590929635

[8] A. Moshiri and A. M. A. Hemmatyar, "OPC UA over TSN (time sensitive network) for vertical and machine to machine communication," in *2023 9th International Conference on Control, Instrumentation and Automation (ICCIA)*. IEEE, 12 2023, pp. 1–6. doi: 10.1109/ICCIA61416.2023.10506350 . [Online]. Available: https://ieeexplore.ieee.org/document/10506350/

[9] J. Wang, Y. Ma, L. Zhang, R. X. Gao, and D. Wu, "Deep learning for smart manufacturing: Methods and applications," *Journal of Manufacturing Systems*, vol. 48, pp. 144–156, 07 2018. doi: 10.1016/j.jmsy.2018.01.003 . [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0278612518300037

[10] L. D. Xu, E. L. Xu, and L. Li, "Industry 4.0: State of the art and future trends," *International Journal of Production Research*, vol. 56, no. 8, pp. 2941–2962, 2018. doi: 10.1080/00207543.2018.1444806 .

[11] A. v. d. Oord, S. Dieleman, H. Zen, K. Simonyan, O. Vinyals, A. Graves, N. Kalchbrenner, A. Senior, and K. Kavukcuoglu, "WaveNet: A generative model for raw audio," 09 2016. doi: 10.48550/arXiv.1609.03499 . [Online]. Available: http://arxiv.org/abs/1609.03499

[12] A. Becerra, J. I. De La Rosa, and E. Gonzalez, "A case study of speech recognition in spanish: From conventional to deep approach," in *2016 IEEE ANDESCON*. IEEE, 10 2016, pp. 1–4. doi: 10.1109/ANDESCON.2016.7836212 . [Online]. Available: http://ieeexplore.ieee.org/document/7836212/

[13] G. Santoso, J. Setiawan, and A. Sulaiman, "Development of OpenAI API based chatbot to improve user interaction on the JBMS website," *G-Tech: Jurnal Teknologi Terapan*, vol. 7, no. 4, pp. 1606–1615, 10 2023. doi: 10.33379/gtech.v7i4.3301 . [Online]. Available: https://ejournal.uniramalang.ac.id/index.php/g-tech/article/view/3301

[14] E. Adamopoulou and L. Moussiades, "An overview of chatbot technology," in *Artificial Intelligence Applications and Innovations*, I. Maglogiannis, L. Iliadis, and E. Pimenidis, Eds. Springer International Publishing, 2020, vol. 584, pp. 373–383. doi: 10.1007/978-3-030-49186-4_31 . [Online]. Available: https://link.springer.com/10.1007/978-3-030-49186-4_31

[15] R. Klabunde, "Daniel jurafsky/james h. martin: Speech and language processing. an introduction to natural language processing, computational linguistics, and speech recognition," *Zeitschrift fur Sprachwissenschaft*, vol. 21, no. 1, pp. 134–135, 01 2002. doi: 10.1515/ZFSW.2002.21.1.134 .

[16] M. Norda, C. Engel, J. Rennies, J.-E. Appell, S. C. Lange, and A. Hahn, "Evaluating the efficiency of voice control as human machine interface in production," *IEEE Transactions on Automation Science and Engineering*, vol. 21, no. 3, pp. 4817–4828, 07 2024. doi: 10.1109/TASE.2023.3302951 . [Online]. Available: https://ieeexplore.ieee.org/document/10230286/

[17] I. Goodfellow, Y. Bengio, and A. Courville, *Deep learning*. MIT Press, 2016. doi: 10.1007/s10710-017-9314-z .

[18] J. Heaton, "Ian goodfellow, yoshua bengio, and aaron courville: Deep learning: The MIT press, 2016, 800 pp, ISBN: 0262035618," *Genetic Programming and Evolvable Machines*, vol. 19, no. 1, pp. 305–307, 06 2018. doi: 10.1007/s10710-017-9314-z . [Online]. Available: http://link.springer.com/10.1007/s10710-017-9314-z

[19] H. T. Hien, P. N. Cuong, L. N. H. Nam, H. L. T. K. Nhung, and L. D. Thang, "Intelligent assistants in higher-education environments: The FIT-EBOt, a chatbot for administrative and learning support," in *ACM International Conference Proceeding Series*. Association for Computing Machinery, 12 2018, pp. 69–76. doi: 10.1145/3287921.3287937 .

[20] T. B. Brown, B. Mann, N. Ryder, M. Subbiah, J. Kaplan, P. Dhariwal, A. Neelakantan, P. Shyam, G. Sastry, A. Askell, S. Agarwal, A. Herbert-Voss, G. Krueger, T. Henighan, R. Child, A. Ramesh, D. M. Ziegler, J. Wu, C. Winter, C. Hesse, M. Chen, E. Sigler, M. Litwin, S. Gray, B. Chess, J. Clark, C. Berner, S. McCandlish, A. Radford, I. Sutskever, and D. Amodei, "Language models are few-shot learners," 07 2020. doi: 10.48550/arXiv.2005.14165 . [Online]. Available: http://arxiv.org/abs/2005.14165

[21] U. Hunkeler, H. L. Truong, and A. Stanford-Clark, "MQTT-s — a publish/subscribe protocol for wireless sensor networks," in *2008 3rd International Conference on Communication Systems Software and Middleware and Workshops (COMSWARE '08)*. IEEE, 01 2008, pp. 791–798. doi: 10.1109/COMSWA.2008.4554519 . [Online]. Available: http://ieeexplore.ieee.org/document/4554519/

[22] J. Imtiaz and J. Jasperneite, "Scalability of OPC-UA down to the chip level enables "internet of things"," in *2013 11th IEEE International Conference on Industrial Informatics (INDIN)*. IEEE, 07 2013, pp. 500–505. doi: 10.1109/INDIN.2013.6622935 . [Online]. Available: https://ieeexplore.ieee.org/document/6622935/

[23] W. Mahnke, S.-H. Leitner, and M. Damm, *OPC Unified Architecture*. Springer Berlin Heidelberg, 2009. doi: 10.1007/978-3-540-68899-0 .

[24] P. Koprov, A. Ramachandran, Y.-S. Lee, P. Cohen, and B. Starly, "Streaming machine generated data via the MQTT sparkplug b protocol for smart factory operations," *Manufacturing Letters*, vol. 33, pp. 66–73, 09 2022. doi: 10.1016/j.mfglet.2022.07.016 . [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S2213846322000451

[25] P. Bilancia, J. Schmidt, R. Raffaeli, M. Peruzzini, and M. Pellicciari, "An overview of industrial robots control and programming approaches," *Applied Sciences*, vol. 13, no. 4, p. 2582, 02 2023. doi: 10.3390/app13042582 . [Online]. Available: https://www.mdpi.com/2076-3417/13/4/2582

[26] T. H.-J. Uhlemann, C. Lehmann, and R. Steinhilper, "The digital twin: Realizing the cyber-physical production system for industry 4.0," *Procedia CIRP*, vol. 61, pp. 335–340, 2017. doi: 10.1016/j.procir.2016.11.152 . [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S2212827116313129

[27] V. Villani, F. Pini, F. Leali, and C. Secchi, "Survey on human-robot collaboration in industrial settings: Safety, intuitive interfaces and applications," *Mechatronics*, vol. 55, pp. 248–266, 11 2018. doi: 10.1016/j.mechatronics.2018.02.009 . [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0957415818300321

[28] Y. Zhao, R. Said, N. W. Ismail, and H. Z. Hamzah, "Impact of industrial robots on labour productivity: Empirical study based on industry panel data," *Innovation and Green Development*, vol. 3, no. 2, p. 100148, 06 2024. doi: 10.1016/J.IGD.2024.100148 .

[29] N. Murcia, A. Mohafid, and O. Cardin, "Evaluation methods of ergonomics constraints in manufacturing operations for a sustainable job balancing in industry 4.0," in *Studies in Computational Intelligence*. Springer, Cham, 2021, vol. 952, pp. 274–285. doi: 10.1007/978-3-030-69373-2_19 .

[30] M. Wittmann, "Exploring the effect of anthropomorphic design on trust in industrial robots: Insights from a metaverse cobot experiment," in *2024 21st International Conference on Ubiquitous Robots (UR)*. IEEE, 06 2024, pp. 118–124. doi: 10.1109/UR61395.2024.10597479 . [Online]. Available: https://ieeexplore.ieee.org/document/10597479/

[31] K. Biel and C. H. Glock, "Systematic literature review of decision support models for energy-efficient production planning," *Computers & Industrial Engineering*, vol. 101, pp. 243–259, 11 2016. doi: 10.1016/J.CIE.2016.08.021 .

[32] M. Lorenzini, M. Lagomarsino, L. Fortini, S. Gholami, and A. Ajoudani, "Ergonomic human-robot collaboration in industry: A review," *Frontiers in Robotics and AI*, vol. 9, p. 813907, 01 2023. doi: 10.3389/frobt.2022.813907 . [Online]. Available: https://www.frontiersin.org/articles/10.3389/frobt.2022.813907/full

[33] A. Fuller, Z. Fan, C. Day, and C. Barlow, "Digital twin: Enabling technologies, challenges and open research," *IEEE Access*, vol. 8, pp. 108 952–108 971, 2020. doi: 10.1109/ACCESS.2020.2998358 . [Online]. Available: https://ieeexplore.ieee.org/document/9103025/

[34] Z. Lv, "Digital twins in industry 5.0," *Research*, vol. 6, p. 0071, 01 2023. doi: 10.34133/research.0071 . [Online]. Available: https://spj.science.org/doi/10.34133/research.0071

[35] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, pp. 436–444, 2015. doi: 10.1038/nature14539 .

[36] F. Tao, H. Zhang, A. Liu, and A. Y. C. Nee, "Digital twin in industry: State-of-the-art," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 4, pp. 2405–2415, 04 2019. doi: 10.1109/TII.2018.2873186 . [Online]. Available: https://ieeexplore.ieee.org/document/8477101/

[37] Y. Liu, J. Gu, N. Goyal, X. Li, S. Edunov, M. Ghazvininejad, M. Lewis, and L. Zettlemoyer, "Multilingual denoising pre-training for neural machine translation," *Transactions of the Association for Computational Linguistics*, vol. 8, pp. 726–742, 12 2020. doi: 10.1162/tacl_a_00343 . [Online]. Available: https://direct.mit.edu/tacl/article/96484

[38] F. Tao, Q. Qi, A. Liu, and A. Kusiak, "Data-driven smart manufacturing," *Journal of Manufacturing Systems*, vol. 48, pp. 157–169, 07 2018. doi: 10.1016/j.jmsy.2018.01.006 . [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0278612518300062

[39] A. M. Djuric, R. J. Urbanic, and J. L. Rickli, "A framework for collaborative robot (CoBot) integration in advanced manufacturing systems," *SAE International Journal of Materials and Manufacturing*, vol. 9, no. 2, pp. 457–464, 2016. doi: 10.4271/2016-01-0337 .

[40] C. Bartolini, C. Santos, and C. Ullrich, "Property and the cloud," *Computer Law & Security Review*, vol. 34, no. 2, pp. 358–390, 04 2018. doi: 10.1016/j.clsr.2017.10.005. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0267364917301681
[41] L. J. Wells, J. A. Camelio, C. B. Williams, and J. White, "Cyber-physical security challenges in manufacturing systems," *Manufacturing Letters*, vol. 2, no. 2, pp. 74–77, 04 2014. doi: 10.1016/J.MFGLET.2014.01.005.
[42] R. Zhao, R. Yan, Z. Chen, K. Mao, P. Wang, and R. X. Gao, "Deep learning and its applications to machine health monitoring," *Mechanical Systems and Signal Processing*, vol. 115, pp. 213–237, 01 2019. doi: 10.1016/j.ymssp.2018.05.050. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0888327018303108
[43] A. Thelen, X. Zhang, O. Fink, Y. Lu, S. Ghosh, B. D. Youn, M. D. Todd, S. Mahadevan, C. Hu, and Z. Hu, "A comprehensive review of digital twin – part 1: Modeling and twinning enabling technologies," 09 2022. doi: 10.48550/arXiv.2208.14197. [Online]. Available: http://arxiv.org/abs/2208.14197
[44] A. Kusiak, "Smart manufacturing," *International Journal of Production Research*, vol. 56, no. 1, pp. 508–517, 01 2018. doi: 10.1080/00207543.2017.1351644.
[45] E. Matheson, R. Minto, E. G. G. Zampieri, M. Faccio, and G. Rosati, "Human-robot collaboration in manufacturing applications: A review," *Robotics*, vol. 8, no. 4, p. 100, 12 2019. doi: 10.3390/robotics8040100. [Online]. Available: https://www.mdpi.com/2218-6581/8/4/100
[46] M. Sauter, J. Barthelme, C. Müller, and F. Liebers, "Manual handling of heavy loads and low back pain among different occupational groups: results of the 2018 BIBB/BAuA employment survey," *BMC Musculoskeletal Disorders*, vol. 22, no. 1, p. 956, 12 2021. doi: 10.1186/s12891-021-04819-z. [Online]. Available: https://bmcmusculoskeletdisord.biomedcentral.com/articles/10.1186/s12891-021-04819-z
[47] A. Tripathy, J. Van Deventer, C. Paniagua, and J. Delsing, "OPC UA service discovery and binding in a service-oriented architecture," in *2022 IEEE 5th International Conference on Industrial Cyber-Physical Systems (ICPS)*. IEEE, 05 2022, pp. 1–7. doi: 10.1109/ICPS51978.2022.9816880. [Online]. Available: https://ieeexplore.ieee.org/document/9816880/
[48] J. Rigelsford, "Industrial robotics technology, programming and application," *Industrial Robot: An International Journal*, vol. 26, no. 1, 02 1999. doi: 10.1108/IR.1999.04926AAE.003.
[49] OpenAI, "Gpt-4 technical report," 2024. [Online]. Available: https://arxiv.org/abs/2303.08774
[50] ——, "Overview of openai assistants," https://platform.openai.com/docs/assistants/overview, 2025.
[51] R. Bogue, "Europe continues to lead the way in the collaborative robot business," *Industrial Robot*, vol. 43, no. 1, pp. 6–11, 01 2016. doi: 10.1108/IR-10-2015-0195.
[52] Y. Lu, H. Zheng, S. Chand, W. Xia, Z. Liu, X. Xu, L. Wang, Z. Qin, and J. Bao, "Outlook on human-centric manufacturing towards industry 5.0," *Journal of Manufacturing Systems*, vol. 62, pp. 612–627, 01 2022. doi: 10.1016/j.jmsy.2022.02.001. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0278612522000164
[53] A. Misra, A. Agrawal, and V. Misra, "Robotics in industry 4.0," in *Handbook of Smart Materials, Technologies, and Devices: Applications of Industry 4.0: Volume 1-3*. Springer, Cham, 01 2022, vol. 3, pp. 2021–2055. doi: 10.1007/978-3-030-84205-5_68.

Francisco Antonio Lloret Abrisqueta is an Industrial and Automatic Electronic Engineer from the Technical University of Cartagena (UPCT), currently pursuing a PhD in Industrial Technologies with a focus on AI and digital twins. His research centers on intelligent systems for industrial applications, including deep learning and simulation for optimizing manufacturing and predictive maintenance.

Antonio Guerrero Gonzalez is an Associate Professor of Automation and Electrical Engineering and Vice-Rector for Students and Employment at UPCT. His work focuses on Industry 4.0, with research in autonomous systems, collaborative robotics, and AI for industrial automation. He has led various government and industry-funded projects and has published in indexed journals.

Roberto Zapata Martinez is an Industrial and Automatic Electronic Engineer from UPCT and is currently pursuing a Master's in Industry 4.0 with a focus on robotics. His interests include collaborative robotics, autonomous systems, and advanced simulation for intelligent manufacturing systems.