

# **Leveraging Human-Robot Collaborative Systems in Quality 4.0: The Case of Fasteners in Door Assembly**

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## **Abstract**

Based on a current industry necessity identified by the main author as a Quality Management Intern at an automotive industry, the problem of fastener installation in door trim assembly was established for in-depth analysis and improvement. The cited issue results in loss or detachment of fasteners during the transportation of door components between the manufacturing and assembly facilities, generating high warranty costs for the organization. The improvement proposal, executed in a laboratory setting at Universidad Iberoamericana, envisions a Human-Robot Collaborative System to enhance the previous step of placing door trims in final assembly. Human operators validate that fasteners are properly fixed while commanding an UR3 collaborative robot to verify if the correct types of fasteners are utilized for each automobile model. Upon detection, human operators receive real-time notifications, enabling rapid corrective actions to rectify errors before they become a warranty concern. In addition to the UR3 collaborative robot and a 2.5D vision system are harnessed to assure the safety and integrity of human operators performing their duties in open workstations. This method not only mitigates future costs but also highlights the value of human supervision and intervention in conjunction with robotic systems. Instead of replacing human operators, this new approach enables them to achieve superior results by leveraging the precision and efficiency offered by these technologies. Ultimately, the present research project aims to strengthen the relationship between industry and academia with the purpose of solving challenges brought by Industry 4.0.

## **Keywords**

Human-Robot Collaborative Systems, Quality Control, Manufacturing Industry.

## **1. Introduction**

In the ever-evolving landscape of the automotive industry, where the production complexity continues to increase and the zero-defect quality has become non-negotiable, new technologies must be incorporated not only for automation but also to enable smart human-robot collaboration. This presents an ongoing challenge, particularly in addressing quality issues related to fastener installation in door trims, which often lead to costly warranty claims, customer dissatisfaction, and reputational damage.

From direct experience in the quality, reliability, and durability department of the automotive sector, this study addresses one of the main concerns in the industry: missing fasteners in door assemblies during transportation. Although common, this problem remains difficult to detect prior to final assembly without significant human inspection time or the risk of post-delivery failures.

This research explores the use of a human-robot collaborative system as a proactive solution to this quality concern. Using a collaborative robot (cobot) programmed with fastener validation criteria and a vision system for real-time inspections, operators get notifications of inconsistencies before the door trim advances to the final assembly. Allowing immediate rework actions, demonstrating how cobots, rather than replacing human labor, can enhance operator abilities and reduce process variability.

This project was developed in a simulated laboratory environment using tools acquired through both academic and industry experience. Aiming not only to reduce fastener related defects but to reinforce the role of cobots as allies in mass production, proving that collaboration between human abilities and robotic precision is essential for future ready manufacturing.

The paper is structured as follows: Section 2 presents a literature review on Industry 4.0, Quality 4.0, and human-robot collaboration. Section 3 outlines the research methodology. Section 4 describes the experimental setup, including the simulation procedure, vision system, collaborative robot, and operator integration. Section 5 presents and discusses the results, including system validation and improvement proposals. Finally, Section 6 summarizes the conclusions and suggests directions for future research.

## **1.1 Objectives**

The present study addresses specific objectives aimed at strengthening quality assurance in automotive manufacturing through advanced technological integration. These objectives are:

- Contribute to the Quality 4.0 development by providing a replicable model of verification and error prevention in the automotive sector.
- Design and simulate a collaborative inspection system capable of detecting assembly errors before the final door installations.
- Reduce human error and increase detection accuracy through a vision system and a collaborative robot.
- Explore the role of collaborative robots as a tool that enhances human decision-making and ability in different tasks.

## **2. Literature Review**

### **2.1 Human-Robot Collaboration in Automotive Manufacturing**

In recent years, collaborative robots in automotive assembly lines have increased significantly, thanks to their ability to enhance productivity, ensure the safety of the workers to decrease errors. There is evidence in recent studies of how cobots can efficiently manage tasks that require repetitive actions, precision, and ergonomic assistance, especially whenever it is coupled with real-time decision-making systems (Villani et al. 2018) and in shared collaborative workspaces (Ruiz Garcia et al. 2021).

Automotive companies such as Ford and Mercedes-Benz have implemented collaborative robots in interior component assembly and ergonomic operations, such as shock absorber installation and part positioning, laying the groundwork for tasks like fastener verification in door trims (Ford 2016; Reuters, 2024; SAE 2019).

### **2.2 Vision Systems and Fastener Verification**

Vision-guided robotic systems have become a cornerstone in manufacturing, specifically for quality assurance. However, in the context of fastener installation, 2.5D and 3D vision systems are applied for verification, such as type checking, position review, and orientation of parts, thus minimizing errors prior to final assembly (Zebra Technologies 2023; Kim et al. 2023). This kind of system allows real-time feedback and quick corrective actions, helping human operators improve their productivity and enhancing their ability to react to deviations (Liu et al. 2023). These kind of technologies are very valuable in open workstations since safety and accuracy needs to be balanced.

### 2.3 Process Improvement through Quality 4.0 and DMAIC

Referring to quality 4.0, these blends traditional continuous improvement methodologies and digital technologies such as Artificial Intelligence, Internet of Things, robotics, etc. The DMAIC methodology (Define, Measure, Analyze, Improve, Control) enhances the framework, thanks to the robustness, helping to drive structured improvements and validating the effectiveness of technological interventions (George et al. 2005; Pyzdek and Keller 2014). In the automotive industry, this methodology has been successfully used to reduce rework rates, root cause identification, and failures, standardizing robot assisted operations to ensure higher reliability (García and Moyano-Fuentes 2018).

### 2.4 The Role of Cobots as Allies

As the automation evolves, there is growing evidence that robots, particularly collaborative robots, often known as cobots, are not intended to replace human labor, but to enhance it. In manufacturing environments, cobots can handle repetitive, high-precision, or ergonomically stressful tasks, allowing human workers to focus on problem-solving, decision-making, and supervision (Bortolini et al. 2021). This synergy between humans and robots improves process efficiency, reduces physical strain, and cognitive overload. Researchers emphasize that all successful human-robot collaborations are grounded in mutual adaptability. While robots adapt to human variability, humans learn how to guide and optimize robotic behavior (Villani et al. 2018; Kim and Lee 2022). In the context of automotive manufacturing, such collaboration has proven essential for increasing productivity, particularly in response to growing customization of vehicle components and the demand for zero-defect production.

## 3. Methodology

For the development of this study it was used the DMAIC methodology (Define, Measure, Analyze, Improve, Control) illustrated in Figure 1; this methodology is commonly used in Six Sigma projects focused on quality improvement (Kumar et. al 2021; Mittal et al. 2021). This approach was chosen to address the recurring issue of missing fasteners in door trims; this problem was identified during a quality management internship. This methodology guides the development and simulation of a Human-Robot collaborative system in a laboratory environment at “Universidad Iberoamericana”, aiming to prevent the propagation of defects during assembly.

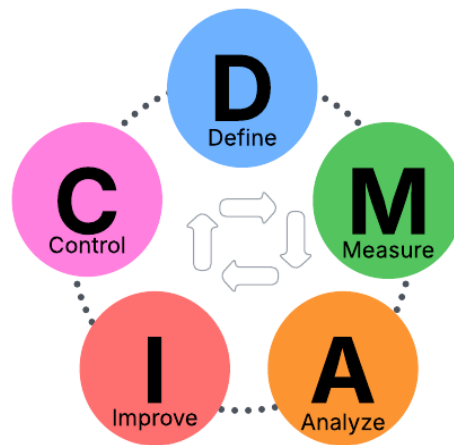


Figure 1. DMAIC methodology

### 3.1 Define

The definition of this issue was based on the recurring warranties claims related to the missing fasteners found during the containerization and after their transportation of the door trim components. These defects, which impacted multiple vehicle programs, were especially prominent in the area of door trims, resulting in high warranty costs and customer dissatisfaction. The project scope was initially limited to fasteners in door trims; However, the proposed system has potential scalability to other parts of the vehicle with fasteners.

### 3.2 Measure

There was established a production line within the university laboratory using a collaborative robot (UR series from Universal Robots) and a 2.5D and 3D vision system. Tests were designed to evaluate if the system will accurately

detect the missing fasteners before the trim was installed in the final assembly; these simulations measured the detection reliability and error identification prior to rework decisions.

### **3.3 Analyze**

Root cause analysis was based on the company's DFMEA (Design Failure Mode and Effects Analysis) database, realizing one of the critical failure modes was the mishandling of door trims during containerization and/or transportation, leading to fastener detachment. Leading the project toward a prevention-based strategy rather than a corrective post assembly solution.

### **3.4 Improvement**

An enhanced process was implemented in the laboratory for the simulation, integrating a Universal Robots collaborative arm programmed with the correct fastener positioning specifications, and with the help of a vision system a cross-referenced system was settled between each component, against its predefined standards. Upon detection of any non-conformity (e.g., missing fastener), the operator received a real-time notification to take corrective action. This prevented the flawed component from advancing into final assembly and eliminated the chance of it reaching the customer.

### **3.5 Control**

To ensure sustainability and replicability of the solution, a system of continuous updates and alerts was embedded within the robot's interface. Although the implementations remain in a simulated environment, potential control mechanisms for industrial use include visual dashboards, automated defect logs, and integration with manufacturing execution systems (MES). Further implementations and work may include process control charts and standardized operating procedures (SOPs), helping the operator interact with the robot.

## **4. Data Collection**

### **4.1 Overview of the Experimental Setup**

This experimental phase was conducted at Universidad Iberoamericana within the Work Study Laboratory and the Quality and Collaborative Robots Laboratory. It was used a UR3 collaborative robot from Universal Robots, which was mounted on a workstation adjacent to the production line of the laboratory. This setup was designed to emulate an actual automotive workflow, the line was programmed to pause temporarily at the robot's station to allow the door trim scanning, this vision system was programmed to detect the presence of fasteners based on spatial reference data uploaded to the robot's logic system.

### **4.2 Simulation Procedure**

The simulation process was completed with a total of 15 door trim inspection cycles, which were divided between three different operators. Each operator followed the same standardized procedure to complete their simulations; however, between each set of five inspections, it was randomly distributed two door trims assembled without missing fasteners, while the other three were purposely modified by removing a fastener in arbitrary locations to simulate real-world variability.

All operators were given the same instructions so as the identical rework protocol upon the alert from the robot. Although individual skill levels varied slightly, there were no observations related to deviations in the inspection workflow. The process remained consistent in all trials: the door trim arrived at the robot's station, the vision system scanned the configuration of the fasteners, upon inconsistencies, the robot triggered a notification (a movement notification), and the operator corrected the issue before the installation.

### **4.3 Role of the Vision System and Cobot**

The vision system is integrated into the robot's programming, which performs scans in its place without requiring the movement of the workstation. Once a missing fastener is detected, the UR3 robot triggers a simple warning to the operator by a waving motion, notifying them of the error. This human-robot interaction allows immediate awareness and intervention without disrupting the workflow of the line.

### **4.4 Operator Involvement**

Operator involvement is a key point in this simulation, highlighting the importance of the collaborative nature of the proposed system.

Once the vision system of the robot detected a missing fastener, this performed a waving motion to notify the detection of an error. Upon the alert, the operator removed the door trim from the pallets of the production line, identified the missing fastener, manually installed a new fastener, and returned the door to the pallet. The entire process was performed manually without confirmation buttons or signal interfaces.

Each of the three operators followed the same procedure for their five simulations. There were no observations of variations of speed or accuracy between them, and the time it took them to perform the corrections ranged from 8 to 17 seconds. The operators relied entirely on the robot's accuracy to initiate the corrective task. This collaborative approach improves the operator's confidence and increases efficiency by making this process more fluid and decreasing the error rate.

#### **4.5 Application of the DMAIC Methodology**

To guide and shape the structured development of the Human-Robot Collaborative System, application was done by way of the DMAIC methodology (Define, Measure, Analyze, Improve, and Control). Six Sigma as well as Quality 4.0 frameworks do find this approach quite fundamental. This strategy drives data so as to reduce quality issues related to fasteners by validating and simulating systems with collaboration.

##### **4.5.1 Define**

The problem was identified at a time when firsthand industrial experience analyzed warranties and found that missing or loose fasteners that were on door trims recurrently caused customer dissatisfaction and also increased cost. A collaborative robot as well as a vision system were to be used to develop one low-cost, non-intrusive system. The system could detect those errors early, improving process reliability without replacement of human labor. Designers simulate actual production situations within a regulated laboratory environment alongside the system, to confirm its viability.

##### **4.5.2 Measure**

Baseline parameters such as operator inspection time, robot station time and also total simulation time were all determined via fifteen separate simulations. Each trial had a detailed time log that separately captured human as well as robotic performance to identify various trends and variability. System responsiveness and operational consistency might be evaluated starting from this foundation, these were the measurements provided for the foundation.

##### **4.5.3 Analyze**

The experimental procedure involved three operators completing five simulations each as well as having a randomized mix of defective and non-defective door trims. Underlying causes in respect to time variation were identified through assessing process consistency, time to correction, and detection accuracy. Cobot alert system effectiveness was validated through each assessment. Data showed that the collaborative approach entirely eliminated error oversight, while operators corrected errors in [that varied slightly depending on individual familiarity.

##### **4.5.4 Improve**

The implementation of the robot's waving motion improved the alert mechanism and was an effective, key part of early test observations. The system's simplicity improved operator engagement as well as rework speed for operators. Wide-ranging training or more digital interfaces were not at all needed owing to such simplicity. In Section 5.3, future ideas for improvement such as color recognition and also multimodal alerts were identified and were discussed too.

##### **4.5.5 Control**

Although the system was tested in a lab environment, monitoring its core parameters ensured repeatability across all trials robot alert reliability, vision consistency, and operator response. Consistent outputs were maintained throughout the process via ensuring uniform operator instructions as well as standardizing the robot's behavior. Section 5.4 Validation discusses instances of replication in actual real-world settings, which the control phase has supported. The control phase documented also the method and simulation parameters.

## **5. Results and Discussion**

The implementation of a human-robot collaborating system resulted in a perfect detection state across all 15 of the simulations, each operator ran five tests with mixed planted errors and the robot was able to identify the error correctly each time, regardless of which element was missing.

Despite the different levels of skill across all operators, the average time required to fix the error ranged from 8 seconds to 17 seconds. This suggests that the system is both accessible and intuitive, requiring minimal training and maintaining consistency and reliability.

### 5.1 Numerical Results

Numerical data obtained in the 15 simulation trials is presented in Table 1. It includes all five inspections by each of the three operators, comprising two cases with correctly assembled door trims and three with missing fasteners. The system had a 100% detection rate for all defective cases, with the robot alerting the operator each time.

The total process time ranged from 36.00 seconds to 62.48 seconds, averaging 44.92 seconds across all simulations. When an error was detected, the operator time increased up to a maximum of 16.54 seconds (Operator 3, simulation 2) while on non-defective systems, it remained below 5.5 seconds.

Despite this variation, the system maintained consistent performance, reflecting the expected differences due to the learning curve. Nevertheless, all operators successfully completed the task without requiring additional training. Robot times -average of around 21.7 seconds- confirm that performance remained stable across all scenarios, regardless of operator variability. Overall, the data supports the system's effectiveness in enabling human intervention without disrupting workflow.

Table 1. Times per operator in each simulation

| Operator   | Number. of simulation | With error? | Operator Inspection | Inspection station | Robot station | Total time (secs) |
|------------|-----------------------|-------------|---------------------|--------------------|---------------|-------------------|
| Operator 1 | 1                     | Yes         | 11.37               | 18.22              | 22.34         | 51.93             |
|            | 2                     | No          | 5.20                | 9.67               | 21.19         | 36.06             |
|            | 3                     | Yes         | 8.52                | 15.12              | 22.08         | 45.72             |
|            | 4                     | No          | 5.42                | 9.48               | 22.82         | 37.72             |
|            | 5                     | Yes         | 15.49               | 20.13              | 21.24         | 56.86             |
| Operator 2 | 1                     | Yes         | 9.65                | 14.56              | 21.93         | 46.14             |
|            | 2                     | Yes         | 11.89               | 16.76              | 22.10         | 50.75             |
|            | 3                     | Yes         | 9.26                | 14.14              | 21.61         | 45.01             |
|            | 4                     | No          | 4.91                | 11.27              | 21.28         | 37.46             |
|            | 5                     | No          | 5.03                | 10.81              | 20.97         | 36.81             |
| Operator 3 | 1                     | Yes         | 13.47               | 17.98              | 21.01         | 52.46             |
|            | 2                     | Yes         | 16.54               | 23.44              | 22.50         | 62.48             |
|            | 3                     | Yes         | 10.74               | 15.03              | 22.25         | 48.02             |

|  |   |    |      |       |       |       |
|--|---|----|------|-------|-------|-------|
|  | 4 | No | 4.88 | 9.25  | 21.87 | 36.00 |
|  | 5 | No | 4.07 | 10.80 | 21.40 | 36.27 |

## 5.2 Graphical Results

Graphical representation provides a clear view of operator performance and system behavior across different conditions, as shown in Figure 2, operator inspection time varied whether it was with or without the fastener. All operators had longer inspection times when errors existed, confirming the system's ability to direct attention without unnecessary delays in the overall process.

Figure 3 shows the total time required per simulation, illustrating how the appearance of an error results in higher times, but it remains within an acceptable range. Robot times remain steady in all cases, which proves the system's reliability.

Results visually reinforce the conclusion that a human-robot system balances decision making with an automated inspection, providing real-time quality assurance without disrupting the flow.

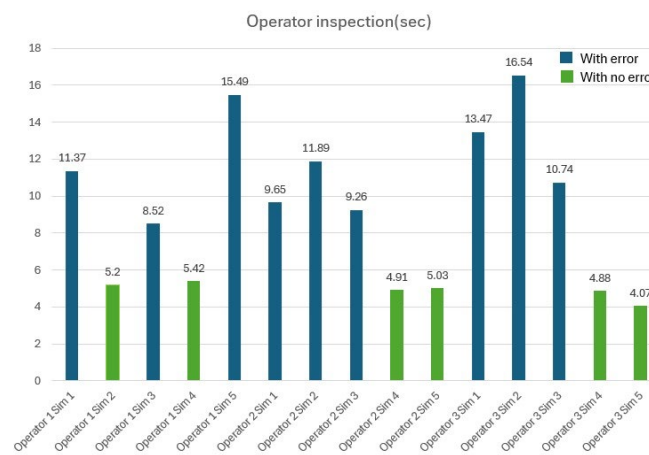


Figure 2. Comparison of errors between operators by simulation



Figure 3. Learning curves of final times by operator.

The following images show the process made by the operators to get the door ready in the assembly line. First, Figures 4 and 5 show manual labor by the operator, inspecting and placing the fastener in the door. Following this, Figure 6



shows the operator placing the door in the assembly line. Subsequently, Figures 7 and 8 show how the robot will interact with the door. Finally, Figure 9 shows the operator removing the door from the assembly line, after the robot is done scanning.



Figure 4. Operator 1 inspecting the door



Figure 5. Operator 1 placing fastener on the door



Figure 6. Operator 2 placing door on the production line





Figure 7. Door on the production line together with the vision system used and the robot.



Figure 8. View of the robot scan.



Figure 9. Operator 2 removing the door from the production line, after scanning.

### **5.3 Proposed Improvements**

Based on the results presented in the previous sections, several improvements can be proposed to increase the effectiveness and scalability for industrial applications. Although a 100% success rate was achieved in detecting errors, variation in operator response time was observed, ranging from 8 to 17 seconds. As illustrated in Section 5.2, this variation reflects differences in operator familiarity and decision-making speed, which impact the total inspection time.

To mitigate this, a proposed improvement is the development of a visual or auditory interface to more precisely guide the operator toward the missing fastener. This would reduce inspection time and minimize delays caused by human factors.

Another key enhancement involves extending the system's vision capabilities to recognize various fastener types and colored components. Currently, the system lacks color detection, and coiled components negatively affect its real-world applicability.

Finally, validation in a real automotive plant is necessary to assess the system under actual operating conditions. Such a test would enable benchmarking against existing inspection standards, aligning with the core motivation described in Section 1.

### **5.4 Validation**

The validation was conducted through a controlled set of 15 simulations in a lab environment, involving three operators and a mix of defective and non-defective door-trims. The system achieved a 100% success rate, identifying all problems and signaling them to the operator.

Operator reaction times remained in a predictable range, and no additional training was required; this indicates that the system was intuitive and does not require mastery of the system to function properly. The robot's performance was stable across all operators.

The results validate the effectiveness of the system in detecting problems early and reducing delays in the production process. It also supports the objectives of Quality 4.0 by combining digital inspection with the adaptability of a human operator in a way that enhances performance. Although it was all conducted in a controlled environment, it showed potential and reliability, while being easy to use, which displays a strong potential for real manufacturing settings.

## **6. Conclusions**

This research successfully demonstrates how the design, simulation, and validation of a Human-Robot collaborative system can enhance quality control in the assembly of automotive door trims. The proposed system integrates a UR3 collaborative robot with a vision-based inspection mechanism, and through operator intervention, effectively identifies missing fasteners prior to final assembly.

Across 15 simulations that involved three different operators, the system achieved a 100% success rate of error detection. Operator response times ranged from 8 to 17 seconds. These results confirm that the use of collaborative robots not only improves defect prevention but also strengthens operator confidence, thereby contributing to a more robust and efficient quality assurance process.

The objectives established at the outset of the study were successfully achieved. The system demonstrated its capability to address one of the most persistent warranty issues in automotive manufacturing—missing fasteners—without requiring operator assistance or disrupting the production workflow. Owing to its flexible programming, simple alert mechanism, and low integration cost, the system presents a viable and scalable solution for industrial environments. Moreover, the results support the key cultural message that robots are not intended to replace workers, but to empower them. Operators showed increased engagement and accuracy, even when using the basic wave alert, clearly illustrating that well-integrated automation can enhance human performance in manufacturing contexts.

Even though the system was under simulated conditions, its success opens the door for future implementations in real production environments. A pilot system in a real automotive plant would represent the next logical step, allowing the validation for complex conditions and real variations such as vibration, lighting, and component diversity. This study

has a hand in contributions to the growing field of Quality 4.0, offering a replicable model for smart and collaborative error detection systems in mass production environments.

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## **Biographies**

**Mariana C. Prantl Padilla** was born in Toluca City in 2001. She studied in a trilingual school until high school, so she has good knowledge of French and an IELTS C1 in English. She also has an Excel and Word Microsoft certification, and good experience in the use of several computer programs. She was born with Ectodermal Dysplasia therefore, her parents founded a non-profit civil association to support people affected by this syndrome. Henceforth, she's been part of many altruistic activities. In 2019, she was the winner of the State of Mexico Youth Award, and in 2020, and Metepec Municipality Youth Award, both of which were given for playing an important role in social responsibility. In 2016, the federal government, through the Ministry of Health, granted her a certificate of participation in voluntary and solidarity actions. Actually, she is studying the 9th semester of Industrial Engineering at Universidad Iberoamericana, Ciudad de México. Last year, she was hired by the Automotive Industry to do an internship that lasted 18 months. She was assigned to the quality area and was in charge of many activities, including those related to guarantees. She was the leader of an OpEx (Operational Excellence) project, which led to the saving of approximately twenty-five thousand hours a year in the introductory teaching of the scholarship holders. It is worth mentioning that this OpEx was nominated for the National Presidency Awards 2023 of the industry.

**Camila Delgadillo** was born in Teziutlán, Puebla in 2002. From an early age, her upbringing in an environment surrounded by industrial machines for denim manufacturing sparked her interest in engineering. This passion led her to excel in national mathematics and history competitions between 2011 and 2014, winning several awards, including Enlace knowledge tests. Currently, Camila is in the tenth semester of Industrial Engineering at Universidad Iberoamericana, maintaining a GPA of 9.1. She has expanded her education with advanced courses in Microsoft Excel (VBA, Macros, @Risk), Microsoft Office Word, PowerPoint, Visio, and Project. Additionally, she holds certifications in AutoCAD Inventor, project management with agile methodologies and Lean approaches, and has completed courses in emerging technologies such as artificial intelligence, sustainable energy management, leadership, and decision-making. In 2024, Camila began her professional career at EPNET of Grupo Impact as a PMO Assistant and project documentation for PEMEX tenders, where she played key roles in creating manuals, translating technical documents, and planning projects in various cities across Mexico. She currently works in the Middle Office of People and Culture at Banco Santander, where she is responsible for automating processes for courses and suppliers. Her projects have been recognized as "banking innovation" at the 2024 closing Town Hall, highlighting her contribution to efficiency and innovation in the banking sector.

**Hugo A. Pérez** is currently a professor of the Industrial Engineering Department at the Universidad Iberoamericana in Mexico City. He is an industrial engineer from Instituto Tecnológico de Tuxtla Gutiérrez, México. He holds an MSc in systems engineering from Universidad Autónoma de Nuevo León (UANL), Monterrey, México, and a PhD in Industrial Engineering from Universidad Anáhuac México. He has written articles in prestigious scientific journals and participated as a speaker at national and international conferences. He is the author and co-author of scientific articles on topics such as applied optimization and statistics in industrial engineering, waste collection routing, and credit risk in the banking industry.

**Pablo Segura** is an Adjunct Professor and PhD in Engineering Sciences at Universidad Iberoamericana, Ciudad de México. He holds a Bachelor of Science in Industrial and Systems Engineering from Tecnológico de Monterrey and a Masters Degree in Advanced Manufacturing Engineering from Universidad Iberoamericana, Puebla. Before his career in academia, he gained professional experience in the innovation and product development departments of transnational companies such as T-Systems and Schaeffler Automotive. Mr. Segura has deepened his interest in the globalization subject as an international student of Université Paris I, Panthéon-Sorbonne. Moreover, he has collaborated with the World Economic Forum as Speaker Leader, addressing the 4<sup>th</sup> Industrial Revolution agenda on their meetings in Latin America, Europe, Asia, and the Middle East. His current research work is focused on the anthropocentric collaboration of humans and robots in the manufacturing industry. In this field, Mr. Pablo Segura has published peer-reviewed scientific articles and participated in academic conferences in Canada, Switzerland, and Italy. Additional interests of his are related to the assessment of emergent technologies that aim to augment the capabilities of humans in the workplace.