MSc Business Information Technology
IT Management & Enterprise Architecture
(Thesis)

How prepared are we for artificial intelligence: AI-driven automobile manufacturing & workforce skills

Student: Mohammed Abdul Raqeeb
Student number: 2819775

Supervisors: Hüllman Joschka, Faiza Bukhsh

November 2024

Faculty of Electrical Engineering, Mathematics and Computer Science (EEMCS) & Behavioural Management and social science (BMS)

University of Twente

Contents

Acknowledgment

First and foremost, I extend my deepest gratitude to GOD, who stood by me, gave me the strength to endure challenges, and guided me through this journey. Without His divine support, I would not have been able to persevere through the obstacles and uncertainties that came my way. I dedicate this thesis to my beloved Mother and Father, who have been my pillars of strength and unwavering support throughout this tumultuous journey. Their encouragement, prayers, and sacrifices have been the driving force behind my accomplishments. This journey, akin to a hurricane, tested my resilience, but their belief in me kept me grounded and determined to push forward. A special note of appreciation goes to my first supervisor, Hüllman Joschka, for believing in my potential and for guiding me whenever I needed assistance. His patience, constructive feedback, and continuous support played a crucial role in shaping this research. Without his encouragement, this thesis would not have reached its present form. I am equally grateful to my second supervisor, Faiza Bukhsh, whose guidance became a beacon of light in my darkest moments. When everything seemed uncertain, she provided clarity, motivation, and the direction I needed to continue my work. Her insights and unwavering support have been invaluable in overcoming the challenges I faced. Finally, I extend my deepest appreciation to myself. For every time I stumbled, I found the strength to rise again. For every setback, I pushed forward with determination. This journey has been a testament to my perseverance, resilience, and unwavering commitment to my goals. I am proud of how far I have come and the challenges I have overcome to reach this milestone. To everyone who played a role in this journey, whether through words of encouragement, moments of kindness, or unwavering belief in me; thank you.

-Mohammed Abdul Raqeeb

1.Introduction

1.1 Background

The integration of Artificial Intelligence (AI) in manufacturing has drastically changed the production processes, the workforce and the efficiency of operations in many industries. The use of machine learning, collaborative robots (cobots), predictive maintenance systems and AI-driven quality control tools are transforming traditional workflows in the automotive sector (Demlehner et al., 2021; Mueller & Mezhuyev, 2022). For example, Robotics and IoT-enabled systems advancements have enabled real-time data analytics, predictive maintenance, and autonomous decision making, which have greatly enhanced productivity and reduced operational costs (Hofmann et al., 2017; Jerry A. Madrid, 2023). companies like BMW are the leading in the use of AI driven cobots for complex assembly tasks and showing the way of how human-robot cooperation can reduce mistakes and increase production rates.(Jain & Kulkarni, 2022; Vermesan et al., 2021). However, the adoption of AI in automotive manufacturing has not been uniform throughout the world. Developed regions, including Germany, Japan, and the United States, have taken the lead in AI integration, supported by significant investments in infrastructure and training. In contrast, underdeveloped regions encounter obstacles such as restricted access to advanced technologies, insufficient training resources, and outdated educational curricula (Amejwal et al., 2022; Mueller & Mezhuyev, 2022). For instance, emerging markets in Africa and Southeast Asia frequently depend on manual labour and traditional methods of manufacturing, resulting in an increasing disparity in workforce readiness for AI-driven environments (Cohen & Gal, 2024; Espina-Romero et al., 2024).

The impact of AI is not limited to technological advancements; it requires a significant shift in the skills of the workforce. Traditional roles that emphasize manual assembly and routine tasks are gradually being automated, resulting in the displacement of workers who do not possess the necessary skills to operate, maintain, and troubleshoot AI-driven systems (Moniz et al., n.d.; Sinha & Lee, 2024). Simultaneously, new roles that require data analysis, machine learning expertise, and human-machine interaction are emerging, and demanding constant upskilling and reskilling initiatives (Arena et al., 2021; Madhavaram et al., 2024). For example, predictive maintenance systems, which depend upon AI algorithms to predict machinery failures often require workers to interpret sensor data and manage IoT-enabled tools, such skills are often lacking in underdeveloped regions(Arents et al., 2021; Keleko et al., 2022). In light of these challenges, the adoption of AI provides major opportunities. Case studies from companies such as General Motors illustrate the potential of machine learning to enhance prototyping processes, whereas Tesla's AI-driven assembly lines exemplify the scalability of robotic automation (Benotsmane et al., 2021; Vermesan et al., 2021). Nonetheless, the effectiveness of these technologies is contingent upon the alignment of workforce skills with the changing requirements. Studies indicate that gaps in technical skills, variations across regions, and reluctance to adapt continue to pose significant challenges to the successful integration of AI (Espina-Romero et al., 2024; Sinha & Lee, 2024). Addressing these issues requires a holistic approach that involve industry leaders, educators, and policymakers to make sure equitable access to training and promote workforce adaptability in an era of rapid technological advancement.

1.2 Research Focus

This thesis investigates the readiness of the factory workforce in AI-driven automotive manufacturing environments, specifically focusing on identifying the essential technical skills necessary for factory workers to efficiently operate and collaborate with AI-driven machinery. This thesis investigates the relationship between workforce skills and technological requirements, emphasizing the existing technical skills of factory workers, identifying critical skill gaps, and addressing the challenges posed by regional disparities between developed and developing areas.
This thesis aims to address the research question: "What skills are most important for factory workers to learn and adapt to in AI-driven automobile manufacturing?" By addressing this question, the research aims at delivering actionable insights for industry leaders, educators, and policymakers to bridge the skill gaps and enhance workforce readiness for AI integration.

1.3 Significance of this thesis

This thesis holds significant value for several stakeholders involved in the automotive manufacturing sector. As AI continues to reshape manufacturing processes, understanding and equipping the workforce with the skills they need is crucial to maximize the potential of these AI technologies. The findings from this this will provide evidence-based insights into the technical skills required for workforce readiness, allowing organizations to develop targeted training programs, minimize operational disruptions, and foster effective collaboration between workers and AI-driven machines.

- **For Industry Leaders:** This thesis provides valuable insights into the technical skills necessary for workforce readiness, allowing organizations to develop training programs that minimize operational disruptions, improve productivity, and facilitate smoother transitions during the adoption of AI technologies. Equipping workers with the skills they need enables companies to optimize the use of AI technologies and sustain a competitive advantage in the market.
- **For Educators and Training Institutions:** The findings of this thesis will guide the development of updated educational programs aligned with the evolving demands of the automotive sector. By addressing specific skill gaps through continuous learning frameworks, educators can prepare future workforce to meet AI-driven manufacturing deemed importance level effectively, ensuring their relevance in AI-driven environments.
- **For Policymakers:** This research provides valuable information to update policies and funding initiatives aimed at workforce development. Addressing disparities in workforce readiness, especially between developed and underdeveloped regions, allows policymakers to implement equitable strategies that enhance global competitiveness and promote skill development across different environments.

1.4 Thesis Outline

This thesis is organized to methodically investigate the readiness of the workforce for AI-driven automobile manufacturing, addressing the research question through an organized series of chapters. The journey begins with the Introduction, which defines the context of AI's transformative role in automotive production, outlines the research focus on workforce skills, and undermean s the significance of this thesis for industry leaders, educators, and policymakers. Then the chapter

2 Methodology, this chapter explains the Design Science Research Methodology (DSRM) framework adopted for this thesis, describing its six phases: problem identification, solution objectives, artifact design, evaluation, and communication to make sure methodological rigor and transparency. The next chapter "Literature Review" synthesizes existing research on AI's evolution in automotive manufacturing, key technologies driving automation, and the socio-technical challenges of workforce adaptation. It identifies critical gaps in understanding workforce readiness, establishing the foundation for this thesis's empirical investigation. Subsequent chapters transition to the practical execution of the research. Design and Development elaborate on the creation of the survey instrument, its structure, validation, and deployment across developed and underdeveloped regions, emphasizing its role in evaluating technical proficiency, skill gaps, and critical skills.

The Analysis and Evaluation chapter presents the findings from 50 respondents, employing statistical tools like ANOVA and thematic analysis to analyze regional disparities, skill prioritization, and workforce challenges. This leads into the Discussion, where theoretical insights from the literature are contrasted with empirical data, revealing misalignments between advanced technical aspirations and practical skill needs, as well as the pervasive impact of resistance to change and infrastructural limitations. The thesis then shifts to actionable strategies in Recommendations/Communication, proposing tailored interventions for industry leaders, educators, policymakers, and global associations to bridge skill gaps and foster equitable AI adoption. The Conclusion synthesizes key findings, reaffirms the hypotheses, and reflects on the balance between technological advancement and human adaptability. Finally, the Limitations section acknowledges constraints such as sample size and sector-specific focus, while Future Research Directions advocates for longitudinal studies, cross-industry comparisons, and deeper ethical inquiries to refine workforce strategies in an evolving AI landscape. Together, these chapters form a comprehensive narrative, guiding stakeholders toward fostering a resilient, skilled workforce capable of thriving in AI-driven manufacturing environments.

2.Methodology

This thesis employs the Design Science Research Methodology (DSRM) proposed by (Peffers et al., 2007) to systematically address the research question formed out of the gap identified through the literature review. The DSRM framework structures the research into six phases: (1) problem identification and motivation, (2) objectives of a solution, (3) design and development, (4) demonstration, (5) evaluation, and (6) communication.

The first phase of DSRM is **Problem Identification and Motivation,** it involves defining the research problem and justifying its significance (Peffers et al., 2007). This phase is grounded in the literature review through which significant gap is identified in workforce readiness for the integration of AI. This phase concluded with the research question, emphasizing the importance of bridging the skill gap to make sure efficient AI adoption globally. The second phase is Objectives of a Solution, it defines the goals for addressing the identified problem (Peffers et al., 2007). These objectives make sure alignment with the research question and guide the next phases, focusing on empirical evaluation and practical relevance. The third phase is Design and Development; this phase involves the creation of an artifact aimed at addressing the identified problem (Peffers et al., 2007). The artifact in this investigation is the data gathered through a structured survey instrument that is aimed at evaluating workforce proficiency, identifying skill gaps, and determining essential skills. The survey consisted of three distinct sections:

1. **Current Proficiency:** Evaluates the capability of workers to effectively operate and maintain AI systems.
2. **Skill Gaps:** Recognizes shortcomings in the areas of human-machine interaction and troubleshooting.
3. **Critical Skills:** Reveals the most important technical skills in AI-driven automobile manufacturing.

The survey employed a 7-point Likert scale and was validated through pilot testing and supervisor's feedback. The survey was conducted using Qualtrics, provided by the University of Twente, ensuring anonymity and adherence to ethical standards. The phase 4 is Demonstration, this phase involves applying the artifact to solve the problem (Peffers et al., 2007). Nonetheless, this phase was excluded because of the nature of the artifact (the survey data). Unlike physical prototypes, surveys do not require iterative testing in operational environments. Instead, the focus shifted to data collection and analysis, which are essential to the evaluation phase. Phase 5 "Evaluation", this phase evaluates the artefact's effectiveness (Peffers et al., 2007). Data from 50 respondents were analyzed using statistical tools (JAMOVI, Excel). Descriptive and ANOVA analyses were conducted to compare skill levels and identify gaps between developed and underdeveloped regions. The thematic analysis of qualitative feedback revealed challenges, the findings demonstrated notable differences. The next and last phase is Communication, this phase communicates findings to stakeholders (Peffers et al., 2007). The findings and suggestions will be conveyed to the stakeholders through the recommendations section, as well as to anyone who reads the report.

This thesis follows the DSRM framework to guarantee methodological transparency, align with established design science principles, and offer actionable insights for enhancing workforce readiness in AI-driven manufacturing.

3. Literature review

Phase 1: Problem Identification and Motivation

3.1 AI in Automobile Manufacturing

The integration of Artificial Intelligence (AI) into automobile manufacturing has evolved from early automation in the **1980s** to today's interconnected, data-driven environments, fundamentally altering production processes and workforce roles (Demlehner et al., 2021; Mueller & Mezhuyev, 2022). This shift, driven by advancements in robotics, machine learning, and cyber-physical systems, emphasizes real-time decision-making, predictive analytics, and seamless human-machine collaboration (Vermesan et al., 2021). While these technologies enhance efficiency and precision, they also redefine the competencies required from factory workers, transitioning from manual and repetitive tasks to roles demanding technical proficiency, analytical judgment, and adaptive problem-solving (Hofmann et al., 2017; Sonntag et al., 2021). This current phase is named as the "second machine age" and argued that human cognitive features might be replaced by AI (Moniz et al., n.d.).

As follows, a cursory literature review has been conducted which delves into the profound transformations brought by Artificial Intelligence (AI) in the automobile manufacturing industry. This transformation highlights a critical challenge: as AI-driven systems become integral to manufacturing, the workforce must acquire skills to operate, maintain, and interact with increasingly intelligent tools.

3.2 Technology driven transformation

The automotive manufacturing sector has undergone a profound transformation by integrating technologies such as advanced robotics, artificial intelligence (AI), and data-centric decision-making systems (Bosch et al., 2018; Gros et al., 2020; Hofmann et al., 2017; Matheson et al., 2019; Sonntag et al., 2021). Traditional frameworks like the holistic framework with requirement-driven approach, have been replaced by integrated methods that use machine learning models, deep reinforcement learning algorithms, predictive maintenance solutions, and real-time analytics (Bosch et al., 2018; Gros et al., 2020; Mueller & Mezhuyev, 2022). As a result, factory workers no longer focus only on operational tasks; they must now interpret algorithmic outputs, collaborate with robotic systems, and respond quickly to sensor-driven insights (Hofmann et al., 2017; Matheson et al., 2019; Sonntag et al., 2021). Companies seek greater efficiency, precision, and product quality while maintaining safety and flexibility, making it critical for factory workers including operators, technicians, and supervisors receive comprehensive upskilling (Bosch et al., 2018; Gros et al., 2020; Matheson et al., 2019).

Industry 4.0 and, more recently, Industry 5.0 place humans and technology in closer collaboration, reshaping job responsibilities to include real-time decision-making and algorithmic oversight (Mueller & Mezhuyev, 2022; Vermesan et al., 2021; Zafar et al., 2024).As automotive factories adopt sophisticated sensors, AI-based scheduling, and digital twins, factory workers are expected to handle dynamically updated workflows guided by cloud analytics and machine-learning insights (Bosch et al., 2018; Gros et al., 2020; Hofmann et al., 2017; Matheson et al., 2019). To be proficient in such settings, companies must implement structured learning pathways that teach data interpretation, collaborative robot (cobot) calibration, and safety protocols (Mueller & Mezhuyev, 2022; Sonntag et al., 2021). By doing so, they align innovative technology with best operational practices, promoting both flexibility and on-the-floor reliability (Bosch et al., 2018; Gros et al., 2020).

3.2.1. Cobots: human-robot collaboration and teaming

One of the most noticeable developments in today's automotive plants is the emergence of collaborative robots (cobots), which operate alongside human workers without the traditional safety fencing typical of older industrial robots (Benotsmane et al., 2021; Matheson et al., 2019; Zafar et al., 2024). These devices use built-in force sensors, speed and separation monitoring (SSM), and power and force limiting (PFL) protocols to avoid collisions based on human proximity (Benotsmane et al., 2021; Matheson et al., 2019). As a result, factory workers must learn how to calibrate sensors, adjust force thresholds, and interpret collision alerts, blending fundamental operational knowledge with AI-powered sensor intelligence (Mueller & Mezhuyev, 2022; Sonntag et al., 2021).

(a) (b) (c)

Figure 2: Types of integration; (a) Coexistence; (b) Cooperation; (c) Collaboration (Benotsmane et al., 2021)

- Coexistence: A human and a robot operate in (partially or entirely) shared space without any common objectives.

- Cooperation: Collaboration occurs when a human and an automaton collaborate in a shared space to achieve a common objective

- Collaboration: A collaboration occurs when a human and a robot work concurrently on the same object in the same space.

The impact of these AI powered robots on workers is different based on their job types. Some may find that their roles become more collaborative as robots aid and reduce physical strain. Others may suffer difficulties related to the overemphasis on automation, potentially leading to underutilization of specific skills (Lijffijt et al., n.d.)

Cobots are efficient at versatile tasks, from welding to precise part placement, and they enable quick reconfiguration for different automotive processes (Benotsmane et al., 2021; Matheson et al., 2019). Workers might load a fresh software routine or use a hand-guided teaching mode to shift an assembly robot from attaching door panels to applying adhesives with minimal downtime (Gros et al., 2020; Zafar et al., 2024). This flexibility changes employee skill requirements, as workers become co-developers of cobot procedures rather than simple machine operators (Bosch et al., 2018; Sonntag et al., 2021). As mass customization grows, being able to rapidly reassign cobots becomes a competitive advantage, provided factory workers are trained to carry out these changes safely and efficiently (Matheson et al., 2019; Mueller & Mezhuyev, 2022). Ensuring Human-Robot Collaboration (HRC) follows strict safety standards, including ISO/TS 15066:2016, which sets force thresholds and separation distances for cobots (Matheson et al., 2019). Meeting these standards requires daily checks, sensor recalibrations, and vigilance about any unusual event, all of which depend on thorough workforce training (Gros et al., 2020; Sonntag et al., 2021). Some automotive plants also equip cobots with advanced vision systems that detect body language or component angles in real time (Benotsmane et al., 2021; Zafar et al., 2024). In these situations, assembly-line staff move away from basic operational duties toward "collaborative systems management," ensuring operations, AI inputs, and safety standards intersect appropriately (Mueller & Mezhuyev, 2022). Human-robot teaming (HRT) advances these ideas further by introducing AI models that adapt to an operator's movements, such as their speed or preferred handover angles, so the cobot can adjust its motion trajectory accordingly (Matheson et al., 2019; Zafar et al., 2024). Operators offer constant feedback, refining reward functions or tackling real-time errors if a cobot's path veers from safety norms (Gros et al., 2020; Sonntag et al., 2021). This approach improves production efficiency but only if factory workers grasp the AI concepts behind it and can modify them for practical shop-floor conditions (Bosch et al., 2018; Mueller & Mezhuyev, 2022). Over time, a well-designed partnership may develop, merging human insight with robotic precision (Matheson et al., 2019). Some facilities also employ multi-agent systems that join cobots, Automated Guided Vehicles (AGVs), and AI-based scheduling, thereby increasing the complexity of factory operations (Benotsmane et al., 2021; Sonntag et al., 2021). In these systems, AGVs supply parts to a cobot for assembly, while sensor-based control algorithms manage timing to avert collisions (Bosch et al., 2018; Zafar et al., 2024). Even a slight mismatch in sensor inputs or schedule updates can halt the line, underlining the need for workers who are proficient in multi-agent coordination (Gros et al., 2020; Matheson et al., 2019). Rather than focusing on a single activity, factory workers now monitor a network of machines that learn, adapt, and communicate continuously (Mueller & Mezhuyev, 2022).

3.2.2. AI-driven predictive maintenance

Predictive maintenance (PdM) uses machine learning to forecast equipment breakdowns before they happen, minimizing production delays and reducing maintenance expenses (Bretones Cassoli et al., 2021; Plorin, 2022). Traditional methods relied on fixed schedules for part replacements or lubrication (Bosch et al., 2018; Hofmann et al., 2017). In contrast, today's factories use sensors to track conveyor motors, welding rigs, or hydraulic presses and send live data to AI systems that identify wear patterns (Gros et al., 2020; Sonntag et al., 2021). Factory workers must interpret these system alerts, telling genuine risks apart from false positives, and plan interventions that cause the least disruption (Matheson et al., 2019; Mueller & Mezhuyev, 2022). Unlike rigid preventive methods, PdM merges statistical anomaly detection, time-series analysis, and past failure records to gauge machine condition (Bretones Cassoli et al., 2021; Hofmann et al., 2017). A sudden sensor spike might cause the model to assign a high failure probability, prompting a prompt repair recommendation (Bosch et al., 2018; Gros et al., 2020; Sonntag et al., 2021). Workers trained to use these predictive dashboards can confirm if the threat is real or if sensor drift created a misleading reading (Matheson et al., 2019; Mueller & Mezhuyev, 2022). By blending operational awareness with AI insights, factories avoid severe malfunctions while reducing needless part replacements (Plorin, 2022).

Complex deep learning systems also highlight the need for clear explanations in PdM (Plorin, 2022; Sonntag et al., 2021). A black-box neural network might declare a motor near failure without clarifying why (Bosch et al., 2018; Gros et al., 2020). Skilled factory workers then investigate sensor logs, study operational settings, or revert to more reliable baseline data if recent inputs distort the model (Matheson et al., 2019; Mueller & Mezhuyev, 2022). This human-machine teamwork provides a balanced, proactive approach to equipment upkeep by uniting data-driven forecasts with hands-on troubleshooting (Bretones Cassoli et al., 2021; Hofmann et al., 2017).

3.2.3. Digital twins and Virtual simulations

Digital twins (DTs) have become crucial for optimizing production processes without disrupting active assembly lines (Hofmann et al., 2017; Sonntag et al., 2021; Zafar et al., 2024). By capturing sensor data, machine statuses, and scheduling details in real time, a DT allows on-the-spot simulations for new layouts or task modifications (Bosch et al., 2018; Gros et al., 2020). Properly trained workers can perform "**what-if**" experiments testing innovative cobot placements or new assembly sequences and evaluate the results before making any physical changes (Matheson et al., 2019; Mueller & Mezhuyev, 2022). However, a DT's accuracy depends heavily on precise data inputs and trustworthy models (Hofmann et al., 2017; Sonntag et al., 2021). If the system continually flags non-existent constraints, it may point to sensor calibration or data-mapping issues (Bosch et al., 2018; Gros et al., 2020). Factory workers who are skilled enough review simulation findings, confirm they match real-world performance, and adjust parameters if needed (Matheson et al., 2019; Mueller & Mezhuyev, 2022). This ongoing interplay of data verification and model refinement cuts production times, decreases rework, and boosts flexibility in responding to changing demands (Zafar et al., 2024). When used with collaborative robots or AI-based schedulers, digital twins can predict how new tasks or machine arrangements will affect throughput (Sonntag et al., 2021; Zafar et al., 2024). For instance, a digital twin might forecast a potential collision if a cobot's path crosses an AGV's route (Bosch et al., 2018; Matheson et al., 2019). By adjusting simulation constraints and re-running tests, teams can ensure a smooth physical rollout (Gros et al., 2020; Mueller & Mezhuyev, 2022). This builds a proactive factory environment where data, robotics, and skilled human oversight come together seamlessly (Hofmann et al., 2017).

Despite the advantages digital twins bring to process optimization, their effective use depends on a workforce that can handle the complexities of modelling, data interpretation, and simulation analysis (Hofmann et al., 2017; Sonntag et al., 2021). Moreover, factory workers must be able to link digital twin outputs to real-world production constraints, ensuring that recommended changes do not conflict with safety standards, operational timelines, or equipment limitations (Bosch et al., 2018; Gros et al., 2020). This blend of analytical, technical, and operational skills is critical for scaling digital twin technologies in the factories, allowing manufacturers to benefit from proactive planning and faster response times while maintaining high levels of quality and efficiency (Matheson et al., 2019; Sonntag et al., 2021).

3.2.4. AI-based quality control and inspection

Quality assurance (QA) practices increasingly apply machine learning tools, such as convolutional neural networks (CNNs), to identify subtle surface defects or minor welding flaws (Hofmann et al., 2017; Mueller & Mezhuyev, 2022; Sonntag et al., 2021). Once detected, operators must decide whether to stop production or if the AI has overreacted to harmless variations (Matheson et al., 2019; Zafar et al., 2024). This method links operational expertise with data-driven judgments, ensuring prompt responses to true defects (Bosch et al., 2018; Gros et al., 2020). Modern quality control frameworks can extend to the entire assembly line, relying on cameras, laser profilers, and thermal sensors for continuous checks (Bosch et al., 2018; Gros et al., 2020; Sonntag et al., 2021). If sensor data indicates an unusual reading perhaps a dimensional mismatch, then the AI system triggers a more detailed inquiry (Matheson et al., 2019; Mueller & Mezhuyev, 2022). Skilled factory workers interpret these alerts, validate the readings, and address problems quickly by combining operational knowledge with data-based understanding (Hofmann et al., 2017; Zafar et al., 2024).

Realizing the full potential of AI-driven quality control requires a workforce capable of aligning advanced analytics with everyday manufacturing realities (Bosch et al., 2018; Gros et al., 2020). Employees need comprehensive training in sensor calibration, data interpretation, and machine learning fundamentals so they can distinguish between minor, non-critical deviations and serious defects (Hofmann et al., 2017; Matheson et al., 2019). This blend of technical and operational know-how allows workers to confirm an AI model's accuracy, make effective real-time decisions about production adjustments, and guide further analysis when anomalies arise (Mueller & Mezhuyev, 2022; Sonntag et al., 2021). Ultimately, Skilled operators are essential in utilizing automated inspections and augmented reality interfaces to ensure product quality, navigate complexities, and maintain a seamless workflows. In some factories, augmented reality (AR) and virtual reality (VR) overlays AI-based defect indicators directly onto physical products (Benotsmane et al., 2021; Zafar et al., 2024).

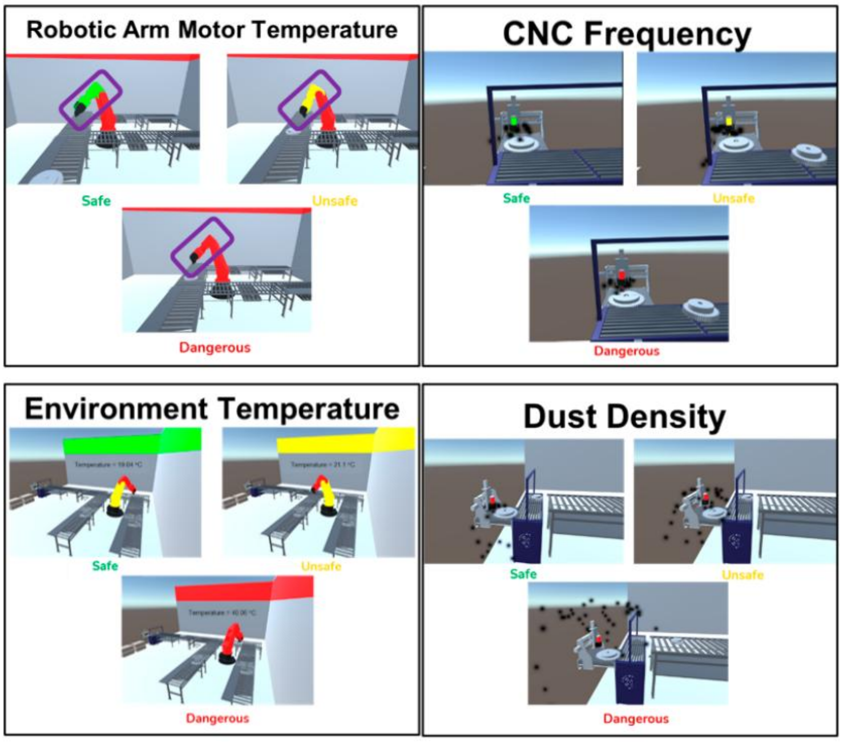

Figure 3: Examples of the visualization of elements in the system using VR (Giordano et al., 2022)

VR can help human workers understand the skills of robots and learn safety procedures, these environments allow for risk-free exploration and learning, reducing the need for on-the-job training that may disrupt production as shown in figure 3. It shows various safety monitoring parameters, it is divided into four main sections, each highlighting a different aspect of industrial monitoring for maintaining safe conditions (Giordano et al., 2022).

1. **Robotic Arm Temperature:** This section provides an overview of the temperature conditions of a robotic arm's motor. The graphic uses a color-coded system wherein the green colour

indicates safe conditions, yellow colour indicates unsafe conditions, and red is used for dangerous conditions.

2. **CNC Frequency:** This segment shows the frequency at which a CNC (Computer Numerical Control) machine operates. Again, a colour code is used to separate the images into safe, unsafe, and dangerous frequencies. By keeping an eye on the frequency, it can be made sure that the machine stays within safe limits and doesn't break down or overload.
3. **Environment Temperature:** Here, the focus is on the ambient temperature of the surrounding environment where the machinery operates. It shows three levels of temperature with corresponding safety status. This monitoring is crucial for maintaining a good working environment and making sure that people and equipment aren't put through harsh conditions.
4. **Dust Density:** This part of the image highlights the concentration of dust in the environment. Similar to the other sections, this one has lights that show when the amount of dust density is safe, unsafe, or dangerous. High dust levels can be harmful to the health and slow down machines effecting on its performance, making this a critical monitoring point.

This helps workers spot potential defects and measure their seriousness (Matheson et al., 2019; Sonntag et al., 2021). Without focused training, however, AR features might overwhelm the workers who are unaccustomed to interacting with digital overlays or misidentified parts (Gros et al., 2020; Hofmann et al., 2017). On the other hand, skilled workers can use AR to speed up root-cause analysis, reducing rework costs and improving production timelines (Bosch et al., 2018; Mueller & Mezhuyev, 2022).

3.2.5. AI-driven supply chain optimization

Automotive supply chains have also changed, thanks to AI's ability to forecast demand swings, enhance logistics, and detect supplier issues (Hofmann et al., 2017; Sonntag et al., 2021). Machine learning models that use historical orders, shipping details, and real-time sensors can predict shortages or plan alternate routes (Bosch et al., 2018; Gros et al., 2020). Skilled workers then interpret these analytics, weigh them against immediate factory realities such as traffic limits or unexpected shipping delays and adjust procurement strategies as needed (Matheson et al., 2019; Mueller & Mezhuyev, 2022).

Inside the plant, Automated Guided Vehicles (AGVs) work with AI-led schedulers to transport items effectively, often coordinating with cobots on the assembly line (Benotsmane et al., 2021; Sonntag et al., 2021). If sensor feeds reveal a looming materials shortage, the system may reallocate resources or reorder tasks to keep the line operating smoothly (Hofmann et al., 2017; Matheson et al., 2019). This setup calls for a team proficient in tracking interactions among various machines, overriding commands when necessary, and handling conflicts before they escalate (Mueller & Mezhuyev, 2022; Zafar et al., 2024). By combining AI-based route optimization with on-site awareness, factory workers help sustain just-in-time production (Bosch et al., 2018; Gros et al., 2020).

Fully extraction of the benefits from AI-driven improvements in supply chain management depends on having workforce with a deep understanding of data analytics, inventory systems, and operational constraints (Bosch et al., 2018; Gros et al., 2020). Workers must be able to interpret predictive models, confirm sensor accuracy, and adjust scheduling logic when sudden disruptions like late deliveries or unexpected part shortages arise (Hofmann et al., 2017; Matheson et al., 2019). This skill set also involves collaboration between logistics personnel and technical staff, ensuring that updates to AGV routes or procurement orders are handled quickly and effectively (Mueller & Mezhuyev, 2022; Sonntag et al., 2021). By building a workforce that can swiftly respond to real-world demands while coordinating

AI outputs, manufacturers can achieve greater stability, reduce downtime, and maintain high throughput across the supply chain (Benotsmane et al., 2021; Zafar et al., 2024).

3.2.6. Workforce skill transformation and adaptation

Cobots, predictive maintenance, digital twins, and intelligent supply networks collectively push automotive workers to move from single-purpose roles to "technologist-collaborators" (Bosch et al., 2018; Gros et al., 2020; Matheson et al., 2019). Beyond operational skills, they must interpret anomaly reports, manage AI-led QA methods, and coordinate AGVs dynamically (Hofmann et al., 2017; Sonntag et al., 2021). These tasks demand not only new technical abilities but also a willingness to learn continuously (Mueller & Mezhuyev, 2022; Zafar et al., 2024). Research by (Bosch et al., 2018) and (Matheson et al., 2019) emphasizes the shift from fixed, requirement-driven processes to flexible, data-driven cycles. Machine learning models, scheduling algorithms, and software updates evolve rapidly, making older skill sets insufficient if they are not routinely refreshed (Gros et al., 2020; Hofmann et al., 2017; Sonntag et al., 2021). In response, many plants use e-learning modules, structured mentorship, or pilot lines where factory workers can try new robotics or analytics systems without disturbing the main production flow (Mueller & Mezhuyev, 2022; Zafar et al., 2024). Industry 5.0 highlights human-focused designs that see AI and robotics as partners alongside human personnel (Benotsmane et al., 2021; Zafar et al., 2024). By helping workers build advanced skills in collaborative robot usage, data visualization, and predictive modelling, manufacturers create a flexible workforce that can adapt processes in real time (Gros et al., 2020; Matheson et al., 2019). As a result, well-planned upskilling turns factory workers into essential contributors to high-quality, agile, and safe production, aligning day-to-day tasks with broader strategic objectives (Bosch et al., 2018; Hofmann et al., 2017; Sonntag et al., 2021).

Although the technologies central to modern factories such as cobots, digital twins, and predictive maintenance have been identified, the specific skill sets workers will need can shift rapidly as new systems emerge (Bretones Cassoli et al., 2021; Lijffijt et al., n.d.). Even proven areas like data analysis, AI system troubleshooting, or sensor calibration may evolve in unexpected ways, requiring factories to monitor ongoing developments in software platforms and operational methods (Bosch et al., 2018; Gros et al., 2020; Plorin, 2022). If companies do not stay informed about these changing requirements, they risk implementing outdated training or leaving workers ill-prepared for challenges such as advanced collaborative robot deployment or real-time analytics for supply chain adjustments (Matheson et al., 2019; Mueller & Mezhuyev, 2022). By adopting forward-looking training strategies like targeted e-learning, simulation-based modules, and regular skill evaluations factories can maintain workforce agility and ensure employees are well-equipped to keep pace with continual technological advancements (Hofmann et al., 2017; Sonntag et al., 2021).

3.2.7. Ethical, Social, and Safety considerations

Beyond operational benefits, AI and robotics present ethical and social challenges. (Lijffijt et al., n.d.) discuss data privacy issues when worker's performance metrics or movement patterns are recorded, while (Matheson et al., 2019) and (Sonntag et al., 2021) emphasize the need for transparency in AI decisions. Workshops in these areas helps factory workers understand their rights, the limitations of data usage, and the responsibility structures overseeing AI tasks (Bosch et al., 2018; Gros et al., 2020). Safety is paramount in collaborative settings where ISO/TS 15066:2016 outlines force and proximity standards for cobots (Matheson et al., 2019). Workers must consistently check sensor calibration, document unusual stop events, and adjust system parameters whenever tasks change (Gros et al., 2020; Sonntag et al., 2021). Additionally, the potential for cybersecurity threats against AI or robotic systems highlights the importance of understanding data traffic, recognizing hacking attempts, and enforcing stringent safeguards (Bosch et al., 2018; Hofmann et al., 2017). Such training combines operational, digital, and ethical knowledge, creating a complete safety culture (Mueller & Mezhuyev, 2022; Zafar et al., 2024).

Social factors also affect job security and changing responsibilities. While advanced robotics automate certain routine tasks, they also create new roles related to AI oversight, cobot programming, and big-data analytics (Matheson et al., 2019; Zafar et al., 2024). Proper upskilling shows how these systems can assist human labour by reducing injuries, enhancing precision, and freeing workers to focus on more complex problem-solving (Benotsmane et al., 2021; Mueller & Mezhuyev, 2022). Without adequate training, factory workers may worry about or resist automation. However, with thoughtful skill development, they can embrace the strategic benefits automation provides (Bosch et al., 2018; Gros et al., 2020; Sonntag et al., 2021).

3.4 Challenges and Opportunities in Workforce Adaptation to AI-driven Manufacturing

The rapid integration of artificial intelligence (AI) into manufacturing has fundamentally reshaped production processes, demanding significant adjustments from workers. These adjustments are not only technical but also socio-economic, creating a category of challenges that directly impact the ability of the workforce to adapt effectively to AI-driven environments (Babashahi et al., 2024; Chimeudeonwo, n.d.; Madhavaram et al., 2024). One of the primary challenges for workers is the increasing need for advanced technical skills to operate and manage AI-driven machinery. Traditional manufacturing, which relied heavily on manual skills and operational experience, has been transformed, workers now interact with technologies like collaborative robots (cobots), Internet of Things (IoT) devices, and advanced vision systems(Chryssolouris et al., 2023; Kaasinen et al., 2022). For example, cobots require workers to understand their programming and troubleshooting, manage uncertainty in interactions, and reprogram tasks as new requirements emerge in the factory (Cohen & Gal, 2024; Sinha & Lee, 2024). Additionally, IoT systems collect and analyze real-time production data, necessitating worker's familiarity with AI-driven predictive maintenance tools and analytical software (Sinha & Lee, 2024). This shift in skill requirements is further exemplified by the adoption of advanced vision systems used for quality assurance. These systems employ machine learning techniques for defect detection, which workers must learn to operate and maintain (Cohen & Gal, 2024; Mueller & Mezhuyev, 2022). To achieve this, continuous education and retraining programs tailored to the demands of AI-driven environments are essential. In underdeveloped regions, this skill gap is exacerbated by the lack of access to relevant education and training infrastructure, highlighting the urgent need for accessible and localized upskilling initiatives (Espina-Romero et al., 2024).

Moreover, the adoption of AI technologies has led to significant changes in job dynamics. Repetitive tasks, such as assembly line roles, are increasingly being automated, displacing many traditional jobs. For instance, predictive maintenance systems can monitor equipment health and pre-emptively schedule repairs without human intervention, significantly reducing the need for maintenance staff (Boavida, 2022; Sinha & Lee, 2024) (Sinha & Lee, 2024). However, while automation displaces some roles, it also creates opportunities for new job categories requiring advanced technical skills, such as data analysts, machine learning specialists, and engineers specializing in AI systems (Arena et al., 2021). This transition undermean s the need for proactive workforce planning to address both job displacement and the emerging demand for high-skilled roles. The regional and demographic disparities in AI adoption further complicate these challenges. In developed countries, workers generally have greater access to training programs and resources that facilitate the transition to AI-enabled roles (Espina-Romero et al., 2024; Mueller & Mezhuyev, 2022). Conversely, underdeveloped nations face significant hurdles due to inadequate infrastructure, limited training facilities, and insufficient investment in education, which widens the gap in workforce readiness (Cohen & Gal, 2024; Sinha & Lee, 2024). Younger workers, particularly those with technical education, are more likely to adapt quickly to these technological changes. However, older workers or those with less formal education may struggle, underscoring the necessity of inclusive training programs that cater to diverse skill levels and demographics (Sonntag et al., 2021).

Resistance to change within organizations adds another layer of complexity. Companies with rigid structures often fail to create environments that encourage adaptation and collaboration with AI systems. Workers accustomed to traditional practices may resist adopting new technologies, driven by fear of job loss or mistrust of automation (Espina-Romero et al., 2024; Sinha & Lee, 2024). This resistance is particularly pronounced in regions where cultural attitudes emphasize the value of human labour over automation(Espina-Romero et al., 2024; Tekic et al., 2019). Addressing this resistance requires fostering a culture of trust and collaboration through transparent communication and employee involvement in AI integration processes. Social and ethical considerations are also critical. AI-driven automation significantly enhances workplace safety by automating hazardous tasks, such as handling heavy lifting, managing dangerous chemicals, and operating in extreme temperatures. These measures reduce the risk of injuries and improve overall workplace conditions (Arena et al., 2021). However, the introduction of AI and robotics also brings new safety concerns that must be addressed through rigorous safety protocols and continuous monitoring (Arena et al., 2021; Sonntag et al., 2021). Additionally, ethical considerations, such as ensuring equitable access to training and addressing disparities in workforce readiness, are vital to fostering a fair transition to AI-driven manufacturing.

The adoption of AI technologies necessitates significant changes in the skill sets of workers in the automobile manufacturing industry. Workers need higher technical skills, particularly in areas like data analysis, machine learning, and the maintenance of advanced systems. Proficiency in operating and maintaining complex machinery such as Cyber-Physical Systems (CPS), Internet of Things (IoT) devices, automated production lines, and AI-driven systems is also (Sonntag et al., 2021; Vermesan et al., 2021). Moreover, the implementation of deep reinforcement learning (DRL) technologies in the car manufacturing process has led to a demand for skills in advanced technologies such as deep Q-learning and Monte Carlo tree search, which optimize processes like re-ordering (Gros et al., 2020). Workers must also develop the capacity to manage and interpret large datasets, understand machine learning models, and optimize analytics to improve production processes (Arena et al., 2021). To equip the workforce with these skills, continuous training programs are needed. This includes educational programs, on-the-job training, and specialized training in AI, machine learning, and robotics (Arena et al., 2021; Druml et al., 2018). The transition from traditional mechanical roles to more technical, analytical positions require upskilling and reskilling programs to help workers adapt to the evolving technological landscape (Arena et al., 2021; Demlehner et al., 2021). Companies must invest in these training initiatives to make sure their employees can manage and maintain advanced technologies effectively. Additionally, by identifying critical influencing factors and benchmarking energy performance, factories can optimize processes, leading to faster production cycles, reduced downtime, and a more efficient use of resources. This can indirectly impact workforce dynamics by reducing the need for manual intervention and increasing reliance on automated systems (Flick et al., 2023). The ongoing demand for higher technical skills, especially in AI-driven systems, undermean s the importance of continuous training programs to make sure that the workforce can adapt to new technologies (Keleko et al., 2022).

Economic factors also play a pivotal role. The cost-benefit analysis associated with implementing AI technologies highlights a substantial initial investment in acquiring and setting up these systems. However, the long-term cost savings from automation including reduced downtime and extended equipment lifespan through predictive maintenance are significant (Arena et al., 2021; Keleko et al., 2022). These economic advantages emphasize the need for organizations to carefully balance upfront costs with long-term benefits, ensuring sustainable adoption of AI technologies.
Labour relations are another critical aspect. The integration of AI and automation technologies impacts labour unions and collective bargaining processes, necessitating changes in labour policies and regulations to address new workforce dynamics. Proactive engagement between employers, employees, and unions is essential to make sure fair labour practices and to address concerns related to job displacement (Arena et al., 2021). By fostering collaboration and implementing equitable policies, stakeholders can create an environment that supports both technological innovation and worker well-being. The integration of AI into manufacturing thus presents a complex interplay of challenges and opportunities.

3.5 Gap

The rapid integration of AI and automation in the automotive manufacturing sector emphasizes the urgent need to address significant workforce-related challenges. While automation improves productivity and optimizes production processes, its effective implementation relies on adequate infrastructure and a skilled workforce. Many companies recognize the necessity of digital transformation but face barriers such as limited access to skilled human resources, knowledge, and suitable technologies (Boavida, 2022; Mueller & Mezhuyev, 2022) (Mueller & Mezhuyev, 2022). The shift towards AI-driven manufacturing has made numerous traditional jobs redundant, highlighting an urgent requirement for the re-skilling of workers to align with AI technologies such as machine learning and collaborative robotics (Cohen & Gal, 2024; Madhavaram et al., 2024). Moreover, it is evident that a single individual can not possess all the necessary skills to succeed in these environments, which undermean s the need for a customized strategy for skill development (Cohen & Gal, 2024). In this evolving landscape, the significance of fostering a culture of continuous education and skill development is crucial for industries to keep pace with rapid evolution of AI (Sinha & Lee, 2024). However, the global competition for AI experts presents additional challenges, with industrial manufacturers competing against tech giants and startups for limited skilled professionals. This talent shortage not only drives up salaries but also forces companies to innovate their hiring strategies and invest in partnerships with academic institutions and startups (Tekic et al., 2019). Furthermore, significant organizational adaptations, including cultural shifts and strategic investments, are necessary to address challenges associated with costs, infrastructure, and workforce (Espina-Romero et al., 2024). Addressing these gaps through targeted skill development initiatives is necessary to prepare workers for the increasingly sophisticated demands of AI-driven manufacturing environments.

(Cohen & Gal, 2024; Madhavaram et al., 2024) To develop an effective workforce for AI-driven automotive manufacturing, it is needed to first identify "**what**" specific skills required, understand "**why**" these skills are necessary, and then determine "**how**" they can be developed. Without a clear understanding of "what" to focus on, efforts to bridge the skills gap risk being misaligned with industry needs. The rapidly evolving dynamics in the automotive sector, driven by AI automation, have rendered many traditional roles obsolete and created a pressing need for re-skilling workers (Cohen & Gal, 2024; Madhavaram et al., 2024)

By answering the question, "What skills are most important for workers to learn and adapt in AI-driven automobile manufacturing?" this research aims to provide the foundational understanding necessary to guide skill development initiatives, ensuring proper alignment with the sophisticated demands of AI-integrated manufacturing processes. Identifying and prioritizing these skills is an essential first step to effectively address workforce challenges and enable successful industry transformation.

3.6 Motivation for Addressing the Problem

The growing influence of artificial intelligence (AI) in automobile manufacturing has drastically reshaped traditional production techniques, placing substantial pressure on workers to acquire more sophisticated skills. While AI-driven systems boost efficiency and automate repetitive tasks, their widespread adoption often causes existing skill sets insufficient (Boavida, 2022; Mueller & Mezhuyev, 2022) (Mueller & Mezhuyev, 2022). As manufacturers increasingly depend on technologies such as predictive maintenance, real-time data analytics, and collaborative robots, workers are required to interpret sensor readings, troubleshoot machine-learning algorithms, and safely engage with autonomous robots (Benotsmane et al., 2021; Matheson et al., 2019). These elevated technical requirements coincide with regional and demographic disparities, as well as organizational resistance from employees worried about job displacement (Espina-Romero et al., 2024; Tekic et al., 2019). Therefore, the research question "What skills are most important for factory workers to learn and adapt in AI-driven automobile manufacturing?" addresses an urgent need to clarify which skills will enable workers to remain resilient and efficient in AI-driven manufacturing environment (Arena et al., 2021; Cohen & Gal, 2024; Madhavaram et al., 2024). The need for a solution arises from the profound social and economic consequences of rapid integration of AI in manufacturing. While automation can improve occupational safety by taking over hazardous jobs and extending equipment lifespans through predictive maintenance, it also eliminates the need for workers who lack the advanced technical backgrounds needed to operate, maintain, or program emerging machinery (Babashahi et al., 2024; Chimeudeonwo, n.d.). However, this same shift creates opportunities for highly skilled data analysts, AI specialists, and robotics engineers (Arena et al., 2021). Bridging the growing gap between existing workforce skills and evolving technological demands requires structured retraining initiatives, inclusive workplace cultures that encourage adaptation, and equitable access to education (Kaasinen et al., 2022; Sinha & Lee, 2024). In the absence of well-defined strategies, organizations may encounter inefficiencies, safety lapses, and lack of expertise that could undermine the overall potential of AI-driven manufacturing (Demlehner et al., 2021; Sonntag et al., 2021).

The **Unified Theory of Acceptance and Use of Technology** (UTAUT) has been used for decades as a foundational framework for examining user acceptance of various technologies, but the shift towards artificial intelligence (AI) applications and Internet of Things (IoT) devices requires a reconsideration of its scope and adaptability. Since the last major revision in 2012, UTAUT 2 has generally maintained the same factors, such as performance expectancy and effort expectancy, even though technological advancements have grown far more diverse. According to, the increase in AI- and IoT-oriented products in recent years demands that researchers ask whether UTAUT 2 fully accounts for the unique attributes of these next-generation tools. The study by (Kessler & Martin, n.d.) concludes with a clear call to introduce an improved or completely new version of UTAUT capable of addressing technologies that demonstrate dynamic behaviours and continuous learning key characteristics of AI-driven systems. The necessity for this expansion is emphasized by extensive studies on technology acceptance, indicating that contextual factors significantly impact the situation when the technology involved is evolving in real time or drastically alters user interaction (Malatji et al., 2020; Or, 2023). This perspective aligns with the observations of (Xue et al., 2024), who argued that "underutilizing emerging theoretical models can limit our understanding of how users adopt innovative platforms", particularly in fields that differ extensively from the stable environments in which UTAUT was originally validated. In highly dynamic AI environments, technology constantly adapts to user input, learns from operational data, and modifies its own processes in ways that traditional, more static tools do not(Kessler & Martin, n.d.). As a result, constructs such as performance expectancy may fluctuate depending on how effectively the AI refines its performance over time, while expectation of effort might shift if the system's learning algorithms become more user-friendly or similarly more complex. Additionally, AI's capacity to automate tasks once carried out by humans may increase concerns over job displacement, leading to a higher emphasis on social influence and facilitating conditions two other core determinants in UTAUT than in less disruptive technological disciplines (Bayaga & Du Plessis, 2024; Venkatesh, 2022). This disruption is particularly apparent in industries where AI-enabled automation and robotics have entered at a pace that surpasses organizational readiness, creating unique acceptance barriers that rely on trust, perceived risk, and the broader workforce's willingness to adapt (Kessler & Martin, n.d.; Or, 2023). The likelihood for AI to tailor itself according to user data is equally significant, suggesting that UTAUT may need to integrate additional predictors or intermediaries that address the dimensions of personalization and privacy concerns, which were not thoroughly examined during the original framework's development (Malatji et al., 2020). The demand for more inclusive and context-sensitive adaptations of technology acceptance models resonates with the findings in (Xue et al., 2024), which suggest that research in higher education is considered inadequate if it does not address the unique needs and attributes associated with new technology implementations. Therefore, testing UTAUT in an AI-driven environment is not just a theoretical exercise, but a necessary evolution of a widely used model. Through a detailed examination of individual responses to the dynamic nature of data-intensive applications, researchers and professionals can enhance acceptance frameworks to better reflect complexities such as adaptive intelligence, the evolution of real-time systems, and changing user deemed importance level. This crucial step makes sure that research findings remain valid as AI continues to reshape industries, confirming that UTAUT (in its current or updated form) can effectively gauge acceptance factors when the technology itself is both the subject and the agent of continuous transformation (Kessler & Martin, n.d.; Xue et al., 2024).

3.7 Research Question and Hypothesis

As discussed in the previous section, "Gap," the transformative impact of artificial intelligence (AI) on automobile manufacturing requires identifying the precise technical skills needed by factory workers. Without this foundational understanding, the integration of AI technologies into manufacturing process risks inefficiencies, operational challenges, and misalignment between workforce skills and technological advancements. The research question, "What skills are most important for factory workers to learn and adapt in AI-driven automobile manufacturing?", is essential for ensuring workforce readiness and optimizing production efficiency in a highly dynamic industrial landscape.

The integration of advanced AI systems such as collaborative robots (cobots), IoT-enabled predictive maintenance tools, and AI-powered quality control mechanisms has primarily reshaped traditional workflows. Factory workers now face demands that go beyond operating machinery, requiring them to interpret real-time data, program and configure systems, and troubleshoot complex automation tools. The justification for this research question is rooted in its focus on bridging the skills gap that AI integration introduces. As highlighted by Cohen and Chalutz, the successful AI-driven manufacturing depends on the alignment of workforce skills with technological systems (Cohen & Gal, 2024). While current studies extensively examine AI's impact on productivity and efficiency, there is a critical lack of focus on the specific technical skills required for effective workforce participation in these environments. For example, (Suhaib Kamran et al., 2022) highlight that training initiatives frequently fail to align with industry demands because of an insufficient understanding of the technological skills that workers need to develop. This thesis addresses this gap by systematically identifying essential technical skills for workers across developed and underdeveloped regions, using a knowledge problem lens as part of the Design Science Methodology framework (Mueller & Mezhuyev, 2022; Peffers et al., 2007).

Hypotheses

The research hypotheses are structured as follows:

1. **H1:** Factory workers require advanced technical skills, such as programming AI systems, interpreting machine-learning outputs, and maintaining IoT-enabled devices, to effectively operate within AI-driven automobile manufacturing environments.
2. **H2:** Identifying specific technical skills for AI-driven manufacturing is crucial for aligning workforce training programs with industry needs, thereby fostering workforce readiness and minimizing skill mismatches.
3. **H3:** There are significant regional disparities in workforce readiness for AI adoption, with underdeveloped regions facing greater challenges due to limited access to technology, inadequate training resources, and outdated educational curricula.

These hypotheses emphasize the importance of skill identification as the foundational step for workforce development. For instance, workers operating AI-powered quality control systems must not only input inspection parameters but also interpret diagnostic results and address operational malfunctions in real time. This multifaceted skill set is indispensable for leveraging AI's full potential, including enhanced efficiency, scalability, and defect reduction in production processes.

Moreover, the research question holds both theoretical and practical significance. On a theoretical level, it contributes to the growing body of knowledge on workforce development in AI-integrated manufacturing environments. Practically, it lays the groundwork for workforce training programs by defining the skills necessary for effective AI adoption. This principle is equally relevant across developed and underdeveloped regions, where understanding local workforce requirements is key to addressing global disparities in AI integration.

By systematically addressing the research question, this thesis aims to bridge the gap between technological advancements and workforce skills, ensuring that factory workers are adequately prepared for the demands of this transformative era.

3.8 Objective

Phase 2: Objectives of a Solution

The second phase defines the goals for addressing the identified problem. These objectives are derived from the insights gathered during the problem identification phase and establish the foundation for designing the artifact (Peffers et al., 2007). In this thesis, the artifact refers to the knowledge derived from the survey, structured to evaluate workforce readiness and identify skill gaps in AI-driven automobile manufacturing environments. The objectives make sure that the artifact aligns with the research question and provides actionable insights to address the defined problem.

The objectives of the solution are explicitly derived from the insights gained through the literature review and the identified gap in workforce readiness. These objectives aim to bridge the gap between the current technical skills of factory workers and the skills required for effective integration of AI technologies in automobile manufacturing.

Objectives-

1. **Assessing Current Technical Skills**: Evaluating the existing technical skills of factory workers in operating, maintaining, and troubleshooting AI-driven machinery, such as cobots, predictive maintenance systems, and AI-powered quality control tools. This objective addresses the first step in understanding the workforce’s current skills, to identify baseline proficiency levels.

2. **Identifying Skill Gaps**: Determining the areas where workers lack proficiency in interacting with and managing AI technologies. The literature review emphasized that skill gaps significantly hinder the effective deployment of AI technologies (Hofmann et al., 2017).

3. **Highlighting Critical Technical Skills**: Identifying the most important technical skills needed for successful workforce adaptation to AI-driven manufacturing environments. By focusing on skills such as programming, data analysis, and human-machine interaction, this objective makes sure alignment with industry demands for AI integration.

4. **Exploring Regional Disparities**: Analyzing differences in workforce readiness and technical skills between developed and underdeveloped regions. Literature review revealed stark disparities in access to training and technological resources, making this objective crucial for promoting equitable workforce development.

5. **Providing Recommendation:** Providing evidence-based recommendations to guide industry leaders, educators, and policymakers in addressing skill gaps and improving workforce readiness. This objective ties directly to the research question, offering practical solutions for stakeholders to bridge the identified gaps.

These objectives collectively address the research question “**What skills are most important for factory workers to learn and adapt to in AI-driven automobile manufacturing?**”. Each objective makes sure a comprehensive understanding of workforce readiness and aligns with the overarching goal of supporting the successful integration of AI technologies in manufacturing environments.

4. Design and Development

Phase 3: Design and Development

This phase involves creating an artifact to address the problem (Peffers et al., 2007)The artifact in this study is data gathered through a structured survey instrument designed to evaluate workforce proficiency, skill gaps, and critical skills. This phase makes sure that the artifact is tailored to meets the objectives established in the second phase. It includes designing a survey instrument capable of evaluating workforce readiness, identifying skill gaps, and highlighting critical technical skills required for AI-driven automobile manufacturing environments.

4.1 Design

1. **Structure of the survey:** The survey was designed to address the core objectives of the research and was structured into three distinct sections. The first section, **Current proficiency**, focused on assessing the existing technical skills of factory workers. The second section, **Skill Gap**, aimed at identifying underdeveloped or missing skills that hinder effective collaboration with AI technologies. Finally, the third section, **Critical Skills**, explored the essential technical skills required for successful adaptation to AI-driven manufacturing environments. Each section is meticulously designed to align with the objectives to deliver comprehensive insights into workforce readiness.

2. **Question Design:** Each section of the survey contained 11 to 15 questions, formulated based on insights from prior research and practical industry requirements. The questions were formulated to gather both qualitative and quantitative data, thereby ensuring a comprehensive approach to data collection. All of the quantitative questions employed a seven-point Likert scale, allowing respondents to choose their level of agreement with various questions and statements, thereby enabling nuanced analysis of workforce skills and gaps.

3. **Key Focus Areas:** The survey's key focus areas included **Technical Proficiency**, where questions evaluated skills related to operating, maintaining, and troubleshooting AI-driven machinery. Another focus area was the **Gap in Human-Machine Interaction**, which assessed worker's ability to collaborate effectively with technologies such as cobots. Additionally, the survey explored **Important Skills for Workers**, with items addressing the use of predictive maintenance systems, AI-powered quality control tools, and data analysis.

4.2 Survey Development Process

The survey development process was structured into three main stages. **Initial Drafting** involved crafting questions based on gaps identified in the literature review and aligning them with the research objectives. This made sure that the survey comprehensively addressed workforce readiness and skill requirements. Next, the survey underwent **Validation**, where it was reviewed internally by thesis supervisors to confirm its alignment with research goals and methodological rigor. This step was critical in refining the survey's structure and ensuring its academic robustness. The final stage was **Pilot**

Testing, during which the survey was sent to a small group, then the feedback was collected on question clarity, structure, and relevance. Based on this feedback, adjustments were made to improve question phrasing, flow, and overall coherence, resulting in a refined survey ready for deployment. The Survey questions are listed in Table 1.

S. No	Questions
	Section 1
1	Our Factory workers demonstrate the ability to quickly adapt to new AI technologies introduced in the manufacturing process.
2	Our Factory workers can effectively operate basic AI-driven machinery (AI-driven machinery that handle repetitive task and follows a set of defined rules or algorithms to perform a specific task) without requiring constant supervision.
3	Our factory workers have sufficient skills to **operate** AI-driven machinery.
4	Our factory workers have sufficient skills to **interact** with AI-driven machinery.
5	Our factory workers are skilled in **maintaining** AI-driven machinery.
6	Our factory workers have sufficient skills to adjust AI-driven machinery.
7	Our factory workers are proficient in working alongside AI-driven machinery.
8	Our factory workers can interpret feedback from AI-driven machinery.
9	Our factory workers are skilled in using AI-driven predictive maintenance tools.
10	Our factory workers are proficient in using AI-driven quality control systems.
11	Our factory workers can diagnose and troubleshoot minor issues in AI-driven machinery without needing specialist intervention.
12	Our factory workers are knowledgeable about safety protocols related to working with AI-driven machinery.
13	Our factory workers can effectively operate and work alongside AI-driven collaborative robots (cobots).
14	Our factory workers are skilled in using AI-driven tools to assist in production planning and scheduling.

15 Our factory workers participate in training programs to continuously improve their skills in operating AI technologies.

Section 2

1 A noticeable gap exists between our factory workers current skills and the skills required to **operate** AI-driven automated robotic systems used in manufacturing.

2 A noticeable gap exists between our factory workers current skills and the skills required to **maintain** automated robotic systems used in manufacturing.

3 Our factory workers need more skills than what they currently possess to independently carry out maintenance and troubleshooting AI-driven machinery.

4 Our factory workforce needs more training in using AI-driven tools to identify and resolve issues.

5 Our factory workers need to improve their skills to work collaboratively with AI-driven machinery.

6 Our factory workers can optimize AI-driven machinery with their current skill level.

7 Our factory workers have a skill gap between using quality control systems and using AI-driven quality control systems.

8 Our factory workers lack proficiency in adjusting and inputting parameters in AI-driven machinery.

9 Our factory workers are skilled in collaborating with AI-driven cobots.

10 Our factory workers respond positively to AI technologies.

11 Our factory workers need more opportunities and resources for continuous learning to stay updated on advanced AI technologies (AI technologies that give better outcomes and can be complex to operate).

Section 3

1 Proficiency in operating AI-driven machinery is an important skill for our factory workers.

2 Skills in performing routine maintenance tasks, such as inspecting machinery, calibrating sensors, updating software, and replacing worn components are important for our factory workers.

3 Understanding the operation and control of advanced AI-driven robotic systems, such as collaborative robots (cobots), industrial robotic arms, and autonomous mobile robots (AMRs), is an important skill for our factory workers in AI-driven manufacturing.

4	Proficiency in using machine learning algorithms is an important skill for our factory workers.
5	Skills in using human-machine interfaces (HMIs) are important for our factory workers.
6	Understanding and responding to alerts generated by AI machinery is crucial.
7	Proficiency in using AI-based quality control systems is an important skill for our factory workers.
8	Operating AI-driven collaborative robots (cobots) is an important skill for our factory workers.
9	Entering and adjusting data inputs for AI-driven machinery (such as parameters, sensor settings, or performance metrics) is an important skill for our factory workers.
10	Managing AI-controlled conveyor systems is an important skill for our factory workers.
11	Understanding and implementing safety protocols specific to AI-driven machinery is an important skill for our factory workers.
12	The ability to quickly learn and use new AI-driven machinery is an important skill for our factory workers.
13	Adjusting paths of factory robots is an important skill for our factory workers.
14	Using AI-driven systems for inventory management and materials tracking is an important skill for our factory workers.

Table 1

The Table 1 mentions the list of survey questions that are categorised in section 1 (**Current proficiency**), section 2 (**Skill gap**) and section 3(**Critical skills**) that are answered by the respondents through Likert scale of 1 to 7 where 1 defines "strongly disagree" and 7 defines "strongly agree".

4.3 Tools and Platforms Used

The survey was hosted on Qualtrics, a platform provided by the University of Twente. Qualtrics is selected for its user-friendly interface and robust data security measures, ensuring a seamless experience for respondents and reliable data collection. Anonymity and confidentiality were maintained throughout the process to make sure ethical compliance and encourage honest responses from participants and enhancing the quality and integrity of the collected data.

The survey aimed to deliver comprehensive understanding about the readiness of the workforce over the integration of AI in automobile manufacturing. This lays the groundwork for data collection and analysis, ensuring that the objectives are adequately achieved.

5. Analysis and Evaluation

Phase 5: Evaluation

The evaluation phase examines the effectiveness of the artifact (Peffers et al., 2007). Analysis was conducted on data collected from **50** respondents out of a targeted audience of **756**, using statistical tools such as **JAMOVI** (a statistical analysis software) and **Microsoft Excel**. Descriptive and ANOVA analyses were conducted to compare skill levels and identify gaps between developed and underdeveloped regions, and the thematic analysis is conducted for qualitative feedback.

5.1 Data Collection

The data collection process was conducted over a time frame of two months, using of the Qualtrics platform provided by the University of Twente. The selection of this tool was based on its intuitive interface, robust protocols for data security, and capacity for facilitating large-scale survey administration.
The target population of total **756** participants, including production-related HR professionals, technical and operational managerial roles from both developed and underdeveloped regions. The selection of these individuals was based on their direct involvement in AI-driven manufacturing environment, which guarantees the relevance and applicability of the data collected. Participants were invited through emails, outreach on LinkedIn, and leveraging personal network to enhance the rate of participation. A total of **50** replies were obtained from the intended audience, yielding a response rate of **7%**. Despite the response rate did not meet deemed importance level, the variety of respondents from different geographic areas and professional roles offered significant insights into the current readiness of workers.

The survey ensured the anonymity and confidentiality, avoided collecting any personally identifiable information. The participants were aware of the study's objectives, the use of their data strictly for academic purposes, and their entitlement to withdraw from the study at any point. This ethical approach facilitated adherence to research standards and cultivated trust among participants. The collected data will be analysed in subsequent sections to identify trends, skill gap, and regional disparities, contributing to actionable recommendations for workforce development in AI-driven manufacturing.

5.2 Analysis and Results

The survey data underwent a rigorous process of preparation and analysis to ensure accuracy and consistency. Initially, the raw data was cleaned and organized using Microsoft Excel, involving the removal of incomplete responses, standardization of formats, and resolution of any inconsistencies within the dataset. Once the data was properly structured, it was imported into JAMOVI for both descriptive and ANOVA analysis. Additionally, Excel was utilized for supplementary data processing and calculations where necessary. The combined use of these tools enabled a thorough evaluation of the data, ensuring that the findings were both reliable and inciteful.

The analysis of the collected data is divided into two categories: Developed and Underdeveloped regions. In our context, developed region in this study are defined as those countries that utilize advanced manufacturing AI technologies in automotive manufacturing. These countries are characterized by their high level of technological adoption, innovation, and efficiency in production. In contrast, countries that do not keep pace with technological advancements and rely on less sophisticated manufacturing practices are categorized as underdeveloped countries. This distinction is essential for understanding the differences in skill requirements and workforce readiness between these two groups. A detailed list of the countries classified under each category is provided in Table 2 (Maclure & Russell, 2021; Makhado & Sukdeo, 2018; Selim & Gad-El-Rab, 2024) (Barwick et al.,).

S.NO	Developed countries
1	Australia
2	Canada
3	Germany
4	Japan
5	United Kingdom
6	USA
	Underdeveloped countries
1	Brazil
2	Egypt
3	India
4	Indonesia
5	Nigeria
6	Pakistan
7	Philippines
8	South Africa
9	Vietnam

Table 2

5.2.1 Analysis of Demographics

This section presents the demographic analysis of the **50 respondents** who participated in the survey, categorized into developed and underdeveloped countries.

Metric	Developed Countries	Underdeveloped Countries
Mean Age	35.1 years	37 years
Median Age	30.5 years	36 years

Metric	Developed Countries	Underdeveloped Countries
Minimum Age	27 years	28 years
Maximum Age	47 years	56 years
Standard Deviation	4.6 years	5.32 years

Table 3

As seen in the table 3, The age distribution data shows both commonalities and variations in the respondents from the developed and underdeveloped countries.

In terms of similarities, both groups are mainly composed of mid-career workers as reflected by their median ages of 30.5 years in developed countries and 36 years in underdeveloped countries. Furthermore, the age of the respondents are quite balanced, and most of them are around the same age, putting them in similar career stages.

However, there are differences between the two groups. The average age (Mean) in developed countries is a bit lower at **35.1** years whereas in underdeveloped countries it is **37 years**. Moreover, age category is more constrained in developed countries (27-47 years) than in underdeveloped countries where the category is more extensive (28-56 years), which indicates that the latter have a more diverse population of younger and older workers. This is also supported by standard deviation which is lower in developed countries (4.6 years) than in underdeveloped countries (5.32 years), which means that there is more age variation in underdeveloped nations.

Overall, both groups are similar, mainly composed of mid-career workers. However, respondents in underdeveloped countries tend to be from a broader age category compared to their counterparts in developed countries.

Experience in the currently employed company

Descriptives

	Region	Experience in employed company (Years)
N	Developed	20
	Underdeveloped	30
Missing	Developed	0
	Underdeveloped	0
Mean	Developed	4.05
	Underdeveloped	6.08

Descriptives

	Region	Experience in employed company (Years)
Median	Developed	3.05
	Underdeveloped	6.00
Standard deviation	Developed	2.64
	Underdeveloped	2.68
Minimum	Developed	1.00
	Underdeveloped	1.30
Maximum	Developed	13.0
	Underdeveloped	13.0

Table 4

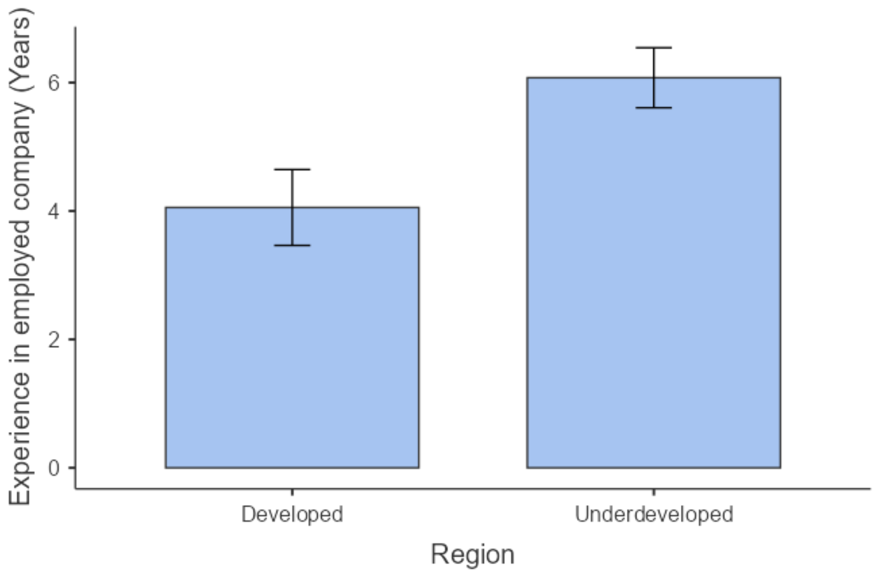

Figure 4

Table 4 and Figure 4 provides an overview of respondent's experience in their current company, distinguishing between managers from developed and underdeveloped countries. The sample size (N) indicates that 20 respondents from developed countries and 30 from underdeveloped countries provided data on their years of experience in the company they are currently working at.

The mean values indicate that managers in underdeveloped countries have significantly **more years of experience** in their current company, averaging 6.08 years, compared to 4.05 years for managers in developed countries. This suggests that managers in underdeveloped regions tend to remain with their employers for a longer duration. The median values further support this finding, with the median in underdeveloped countries being 6.00 years, while in developed countries, it is 3.05 years, reinforcing the trend that managers in underdeveloped countries generally have more experience in their current workplace.

The variability in responses, as indicated by the standard deviation, is slightly higher in underdeveloped countries (2.68) than in developed countries (2.64). This suggests that while most managers in underdeveloped countries have relatively longer years of experience, there are **variations in their lengths of employment**. Similarly, in developed countries, some managers have extensive experience, while others have much shorter years of experience, leading to a comparable spread in responses.

The mean values indicate that managers in underdeveloped countries have spent significantly more years in their current company, averaging 6.08 years compared to 4.05 years for managers in developed countries. This suggests that managers in underdeveloped regions tend to remain with their employers for a longer period. The median values further support this observation, with the median work duration in underdeveloped countries at 6.00 years, while in developed countries, it is 3.05 years. This reinforces the trend that managers in underdeveloped countries generally have longer experience in their current workplace.

In Figure 4, the bar plot provides a visual comparison of these differences, clearly showing that managers in underdeveloped countries have a higher average experience in their current company. The error bars, representing standard errors, indicate that while there is some variation in the responses, the difference between the two regions is distinct. These findings suggest that workforce stability in underdeveloped countries might be higher, with managers staying longer in their roles, whereas managers in developed countries may experience more frequent career transitions within or across organizations.

Gender Distribution

Gender	Developed Countries (%)	Underdeveloped Countries (%)
Male	80%	79%
Female	20%	21%

Table 5

The gender distribution in both developed and underdeveloped countries is quite similar. In both cases, **male respondents are a dominant majority**, 80% in the developed countries and 79% in the underdeveloped countries. In addition, the representation of females is low and consistent between the two regions, at 20% for developed regions and 21% for underdeveloped regions, indicating the same level of gender imbalance in both regions.

Although the two groups are similar in most ways, the slightly higher rate of female participation in the workforce in underdeveloped countries than in developed countries suggests that some regions have more inclusive workplaces. Nevertheless, in both groups, manufacturing is still the male dominant.

Roles:

Role Type	Developed Countries (%)	Underdeveloped Countries (%)
Operational Roles	75%	70%
HR Roles	25%	30%

Table 6

The common and different features of the role distribution across the developed and underdeveloped countries are presented in the table 6. A total of 75% of respondents from developed countries and 70% from underdeveloped countries have operational roles, and respondents with Human Resource (HR) roles are 25% in developed countries and 30% in underdeveloped countries. HR roles are reported at a slightly higher percentage in underdeveloped countries (30%) than in developed countries (25%). This could mean that the less developed regions are paying more attention to the workforce development and management of the areas affected by the changes in order to meet new challenges of AI integration. On the other hand, developed countries are slightly more inclined toward technical capabilities and operational control.

Experience:

Metric	Developed Countries	Underdeveloped Countries
Mean Experience	8.15 years	9.97 years
Median Experience	7 years	10 years
Minimum Experience	3 years	3 years
Maximum Experience	21 years	19 years
Standard Deviation	4.6 years	3.62 years

Table 7

The table 7 reveals the similarities and variations between developed and underdeveloped countries on the experience level of the respondents. Both groups have a minimum experience of **3 years**, meaning that entry-level professionals are found in both areas. Furthermore, the workforce in both areas is a combination of early career and experienced workers, as informed by the category of years of work experience.

However, there are clear **differences** in the mean and median experience in these regions. On average, respondents from underdeveloped countries have more experience (9.97 years). Likewise, the median experience in underdeveloped countries is 10 years, and in the developed regions, it is 7 years, which indicates that the respondents are relatively more experienced. Also, the standard deviation is lower in underdeveloped regions (3.62 years vs. 4.6 years), which means that experience levels of the respondents are more well centered around the mean in underdeveloped countries.

Experience in the company they are currently working in:

Exposure to AI-driven Manufacturing

Worked in AI environments	Developed Countries	Underdeveloped Countries
Yes	95%	94%
Maybe	5%	3%
No	0%	3%

Table 8

The experience within AI-driven manufacturing is almost equal between the two groups. Only 5% of the respondents in developed countries and 3% in underdeveloped countries have never come across AI-based manufacturing, 3% of the respondents in the underdeveloped countries are uncertain if they ever worked in the AI-driven manufacturing environment. This indicates that AI technology is equally adopted in both the economic environments. However, a low but slightly higher percentage of respondents in underdeveloped countries (3%) are certain about having no experience with AI-driven manufacturing compared to none (0%) in developed regions, where **everyone has had some contact with the AI-driven environment**. Furthermore, 5% of the respondents in developed regions were not sure compared to 3% in underdeveloped regions, which means that some people may not always be able to tell AI-related tasks from conventional manufacturing operations.

5.2.2. Analysis of developed countries

In this section, we analyze 20 respondents, the dataset of the developed countries collected through surveys, starting with the analysis of Section 1 (worker's proficiency level of the skills), Section 2 (skill gaps), and Section 3 (deemed importance of the skills by managers), and then conducting a cross-sectional analysis to compare proficiency levels with skill importance, as well as skill gaps with skill importance. Each of these analyses serves a distinct purpose in understanding workforce readiness for AI-driven manufacturing.

The analysis of Section 1 provides insight into which skills workers demonstrate high proficiency in, which skills they are moderately proficient in, and which skills they significantly lack. However, knowing proficiency alone does not indicate whether workers meet industry expectations. To address this, Section 2 examines skill gaps separately, measuring the extent to which workers lack essential AI-related abilities. A skill could have moderate proficiency yet still present a gap if workers are not performing at the level required by AI-driven manufacturing. Similarly, a skill with low proficiency may not necessarily be a priority if it is not critical to production processes. Beyond assessing skill levels and gaps, Section 3 evaluates which AI-related skills managers consider the most important. Some skills may be highly proficient yet not prioritized by managers, while others may have large skill gaps but are not seen as essential. Understanding skill importance ensures that workforce training efforts are aligned with industry needs and AI integration strategies.

5.2.1.2 Sectional analysis of the developed countries:

Section 1:

Figure 4 illustrates the average responses to survey questions in section 1, addressing the skills and abilities of factory workers in AI-driven manufacturing environments. The responses are based on a Likert scale ranging from **1 (strongly disagree)** to **7** (**strongly agree**). The data reflects varying levels of agreement with the statements provided in the survey, highlighting proficiency of skills in factory workers.

In the graph (Figure 4) Skills with a mean between 6 and 7 are classified as **'proficient'** represented by green-coloured bars, skills with a mean between 4 and 6 indicate a **'moderate proficiency'** represented by yellow-coloured bars, skills with a mean between 3 and 4 are categorized as **'lacking proficiency'** represented by category-coloured bars, and skills with a mean below 3 are classified as **'significantly lacking the skill'** represented by red coloured bars.

Additionally, the numerical value in the brackets next to the name of the skills are the mean values of those skills.

Figure 5

Factory workers show high proficiency in only one area that is **participating in AI training programs** with the mean of (6.1) indicating strong engagement in continuous learning, however this is not a skill, most of the skills fall in the moderate category workers show some ability to adapt to AI technologies (4.35) and operate basic AI driven machinery (4.7) but their skills remain below proficient level they can interact with AI Driven machinery (4.1) and interpret AI generated feedback (4.55), and their capabilities in predictive maintenance (4.15) and quality control systems (4.0) five such as that while they Have the skill and understand AI assisted workflows there is still room for improvement, It is similar in their collaborative work with AI driven robots (4.4) where they exhibit competency but not proficiency.

Despite this moderate familiarity workers significantly lack skills in maintaining (3.0) and adjusting AI driven machinery (3.0) as well as in using AI based production planning tools (3.3). This shows that while they can operate AI driven machinery they struggle with technical modifications and optimization. The biggest concern lies in troubleshooting AI driven machinery (2.75) where workers almost lack the skill itself. Without the ability to diagnose or resolve even minor AI malfunctions factory operations risk frequent disruptions.

Section 2:

The graph for Section 2 presents the average responses to survey questions aimed at assessing skill gaps among factory workers in AI-driven manufacturing environments. The questions are measured on a Likert scale from 1 (strongly disagree) to 7 (strongly agree), where higher mean s for specific as shown in the Figure 5 where the skills with a mean between 6 and 7 indicate a high skill gap, represented by red-coloured bars. Skills with a mean between 4 and 6 indicate a moderate skill gap, represented by category-coloured bars. Skills with a mean between 3 and 4 are categorized as having a low skill gap, represented by yellow-coloured bars. Skills with a mean below 3 indicate no significant skill gap, represented by green-coloured bars.

Additionally, the numerical value in the brackets next to the name of the skills are the mean values of those skills.

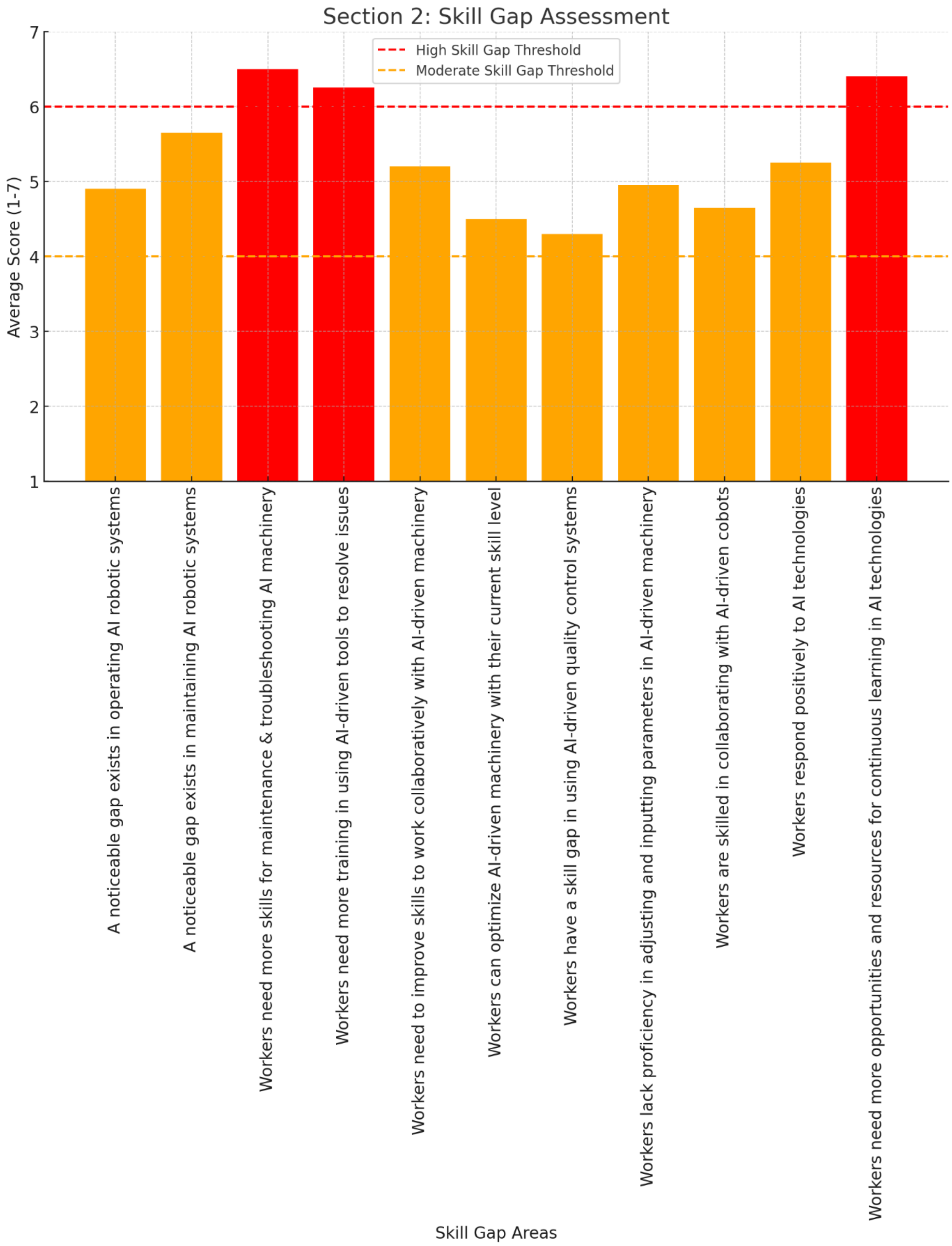

Figure 6

Factory workers exhibit the highest skill gaps (6-7) in three critical areas: maintenance and troubleshooting AI-driven machinery (6.5), training in using AI-driven tools to resolve issues (6.25), and opportunities for continuous learning in AI technologies (6.4). These findings indicate that workers are **not sufficiently skilled** to independently handle AI system failures, diagnose issues, or receive adequate training to bridge these gaps. The severe skill gap in continuous learning (6.4) suggests that workers need more training and resources to stay updated on AI advancements, further hindering their ability to adapt.

A moderate skill gap is considered when the mean of the question responses that fall between 4 and 6. A moderate skill gap is observed in multiple areas, including a noticeable gap in operating (4.9) and maintaining AI robotic systems (5.65), as well as the need for improvement in working collaboratively with AI-driven machinery (5.2). Additionally, workers lack proficiency in adjusting and inputting parameters in AI-driven machinery (4.95) and have gaps in using AI-driven quality control systems (4.3), suggesting that while they have some exposure to AI technologies, their ability to fine-tune and optimize these systems is limited. Interestingly, the assessment that workers can optimize AI-driven machinery with their current skill level (4.5) implies that while some adjustments are possible, the level of effectiveness varies. Importantly, no skills fell below the 4.0 threshold, meaning that workers do not entirely lack the ability in any area. However, the strong presence of high and moderate skill gaps highlights a need for upskilling initiatives.

Without addressing these gaps, manufacturing plants will remain highly dependent on external support for AI maintenance and troubleshooting, leading to increased downtime, inefficiencies, and long-term operational risks.

Section 3:

The graph for Section 3 illustrates respondents" perceptions of the importance of various skills for factory workers in AI-driven manufacturing environments. Each question is measured on a Likert scale from 1 (strongly disagree) to 7 (strongly agree), with higher mean s indicating greater perceived importance as shown in Figure 6 where the skills with a mean between 6 and 7 are classified as highly important represented by green-coloured bars, skills with a mean between 4 and 6 are moderately important represented by yellow-coloured bars, skills with a mean between 3 and 4 are categorized as less important represented by category-coloured bars and skills with a mean below 3 are classified as the least important represented by red-coloured bars.

Additionally, the numerical value in the brackets next to the name of the skills are the mean values of those skills.

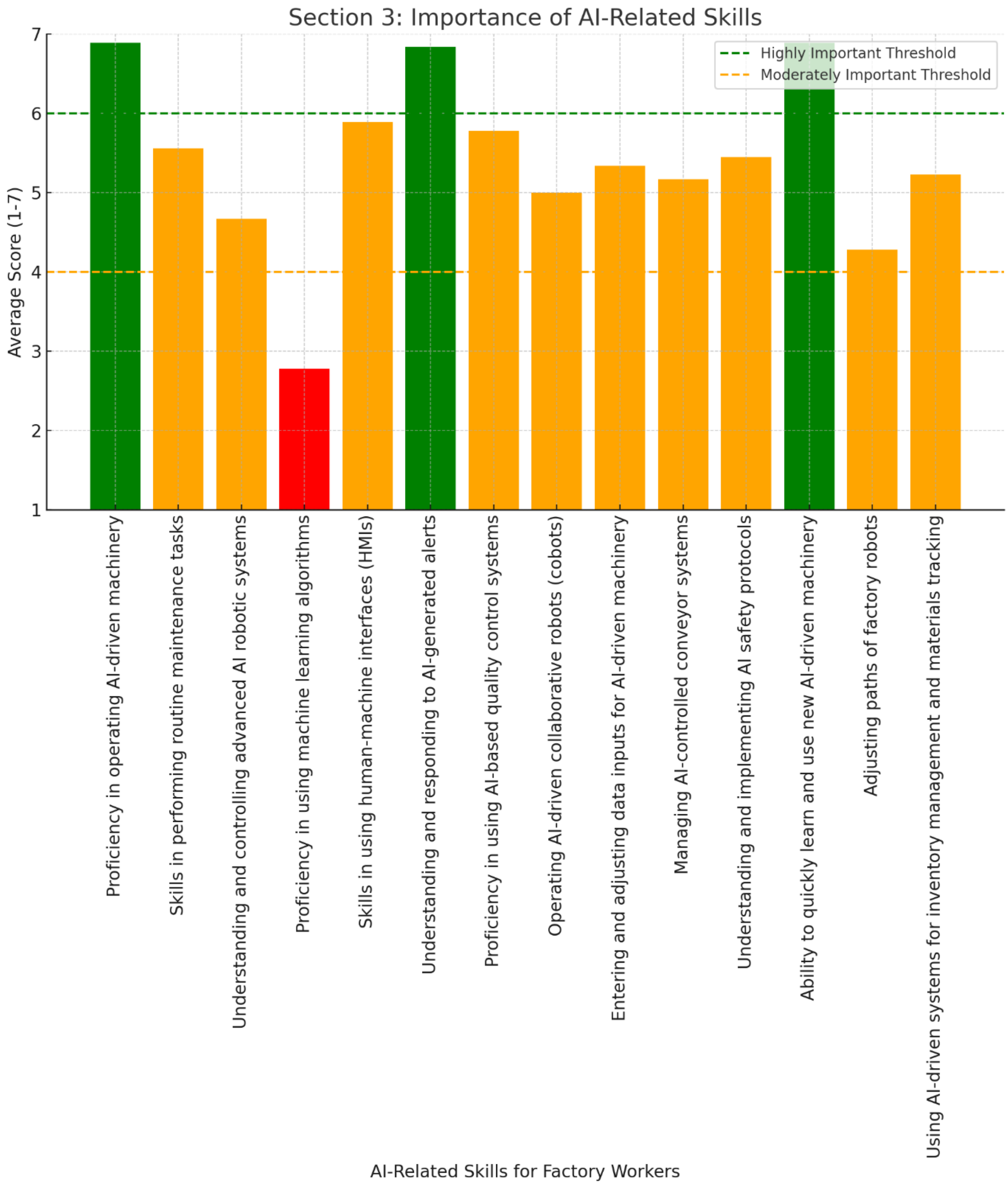

Figure 7

Factory managers identified three skills as highly important for factory workers in AI-driven manufacturing: **proficiency in operating AI-driven machinery** (6.89), **understanding and responding to AI-generated alerts** (6.83), **and the ability to quickly learn and use new AI-driven machinery** (6.89). These findings emphasize that workers must be highly adaptable and capable of efficiently handling AI-integrated manufacturing processes. The emphasis on **learning new AI-driven machinery** suggests that **factories require a workforce capable of quickly adapting to evolving AI systems**, reducing downtime, and ensuring smooth production operations. Additionally, the high mean for **understanding and responding to AI-generated alerts** highlights the critical role of **real-time monitoring and quick decision-making** in AI-driven manufacturing environments.

A moderate level of importance of skill are those with a mean falling between 4 to 6, several technical skills fall into the moderate category, including skills in performing routine maintenance tasks (5.56), understanding and controlling advanced AI robotic systems (4.67), using human-machine interfaces (5.89), proficiency in AI-based quality control systems (5.78), and operating AI-driven collaborative robots (5.00). These findings suggest that while maintenance and interaction with AI systems are important, they are not seen as critically essential as direct AI machinery operation and adaptability. Similarly, the ability to manage AI-controlled conveyor systems (5.17), enter and adjust AI machinery parameters (5.30), and implement AI-specific safety protocols (5.44) are regarded as necessary but not as pressing as operational and alert-handling skills.

Only one skill was considered less important with a mean that falls below 4 is proficiency in using machine learning algorithms (2.78). This finding indicates that factory managers do not expect factory workers to develop AI programming or algorithmic expertise, reinforcing that the focus is on practical AI operation rather than AI development. Overall, the findings highlight a workforce priority: workers must be proficient in operating AI machinery, responding to AI alerts, and quickly adapting to new AI systems. However, they are not expected to engage in complex AI development or algorithmic training.

5.2.1.3 Cross-Sectional Analysis of developed countries

Cross-Sectional analysis of Skill Gaps (Section 1) and Skill Prioritization (Sections 3):

This section presents a cross-sectional analysis between Sections 1 and 3, focusing on the alignment between factory Worker's current skills (Section 1) and the skills identified as important for workers to learn (Section 3). By comparing responses to similar questions from both sections, this analysis aims to identify overlaps, gaps, and priorities in skill development for AI-driven manufacturing environments. The analysis highlights areas where the workforce's existing proficiency aligns with or falls short of the perceived importance of specific skills, as assessed by the respondents. In the figures below, "S" represents the section and "Q" is the question number. Example: S3Q1 represents question 1 from section 3.

Table description: In cross-sectional analysis, the sample size (N) represents the total number of respondents in the 'Developed countries' data set. This indicates how many managers provided responses for a particular skill assessment. For example, if N = 20, it means that the responses from 20 managers were considered when calculating the skill gap or proficiency levels. A larger N generally leads to more reliable and stable estimates, as it reflects a broader perspective from industry professionals.

The mean represents the average of all responses of a particular skill or skill gap or importance of a skill. It provides a central value that summarizes the overall trend of responses. For instance, if the mean for proficiency in operating AI-driven machinery is 4.70, it indicates that, on average, managers rate their worker's ability at a moderate level. The mean helps compare how different AI-related skills are perceived in terms of importance, proficiency, or skill gaps.

The standard deviation (SD) measures the spread or variability of responses around the mean. A low standard deviation indicates that most responses are clustered closely around the mean, meaning there is a general consensus among respondents. In contrast, a high standard deviation suggests that responses are widely spread, indicating differing opinions among managers. For example, if the SD for proficiency in AI-driven machinery is 1.7, it means that while some managers may rate worker's skills as moderate, others perceive them as either much stronger or significantly weaker.

The standard error (SE) reflects how much the mean might vary if the study were repeated with a different sample of managers. It accounts for sampling variability and helps assess the precision of the mean estimate. A lower SE indicates a more reliable mean, suggesting that the responses are more consistent across the sample. For example, if the SE for skill importance is 0.11, it means that the estimated mean is relatively stable and would likely remain close to this value in another study. However, a higher SE (e.g., 0.48) indicates that the mean could fluctuate more if the study were repeated with a different sample.

I. **Cross-sectional analysis on Operating AI-driven Machinery Skills:** In Figure 7, the graph compares the responses of S1Q2 ("Our factory workers can effectively operate basic AI-driven machinery without requiring constant supervision") and S3Q1 ("Proficiency in operating AI-driven machinery is an important skill for our factory Worker's) to evaluate whether the perceived importance of this skill aligns with the actual proficiency of factory workers or not.

Group Descriptives

	Cross sectional analysis	N	Mean	SD	SE
Proficiency in operating AI-driven machinery	**Current proficiency (Section 1)**	20	4.70	1.720	0.385
	Importance (Section 3)	20	6.89	0.471	0.111

Table 9

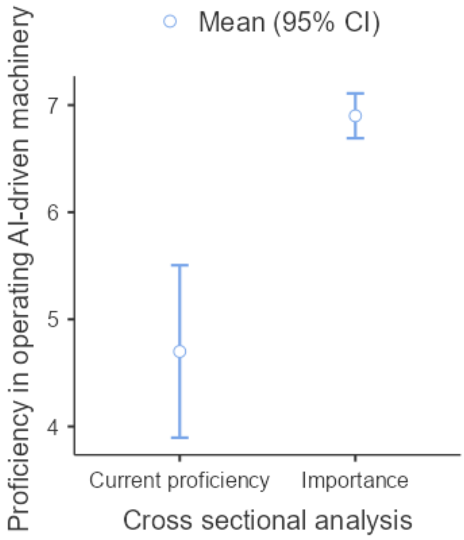

Figure 8

As shown in the table 9 and figure 8, the data indicates that worker's proficiency in operating basic AI-driven machinery without supervision has an average mean of 4.70, while the importance of this skill is rated significantly higher at 6.89. On a 1 to 7 scale, where 7 represents the highest level, this suggests that while workers in developed countries demonstrate a **moderate level of proficiency** in this area, managers still perceive a considerable gap between current proficiency and AI-driven manufacturing needs.

The graph visually reflects this disparity, as the data points for proficiency and importance are clearly separated, with importance positioned substantially higher. The confidence intervals for importance are much narrower than those for proficiency, indicating that managers largely agree on the high importance of this skill, whereas worker's proficiency levels show greater variability. This suggests that some workers in developed countries may be more skilled in AI-driven machinery operation.

A closer look at the standard deviations further highlights this variability. The standard deviation for proficiency (1.720) is significantly higher than for importance (0.471), meaning that there is a wider category of skill levels among workers, with **some performing well while others lag behind**. In contrast, the low standard deviation for importance shows that most managers consistently view this skill as highly necessary for AI-driven manufacturing.

These findings indicate that while factory workers in developed countries have a moderate level of proficiency in operating AI-driven machinery, their skill levels are not yet aligned with the deemed importance level of managers. The consistently high rating for importance suggests that improving proficiency in AI machinery operation remains a priority for manufacturing industries in the developed countries.

II. Cross-sectional analysis on interpreting Feedback from AI-driven Machinery Skills:

As shown in the Figure 9, The graph compares the responses of **S1Q8** ("Our factory workers can interpret feedback from AI-driven machinery") and **S3Q6** ("Understanding and responding to alerts generated by AI machinery is crucial") to evaluate whether the perceived importance of this skill aligns with the actual proficiency of factory workers or not.

Group Descriptives

	Cross sectional analysis	N	Mean	SD	SE
Interpreting feedback from AI-driven machinery	**Current proficiency** **(Section 1)**	20	4.55	1.849	0.4134
	Importance **(Section 3)**	20	6.83	0.383	0.0904

Table 10

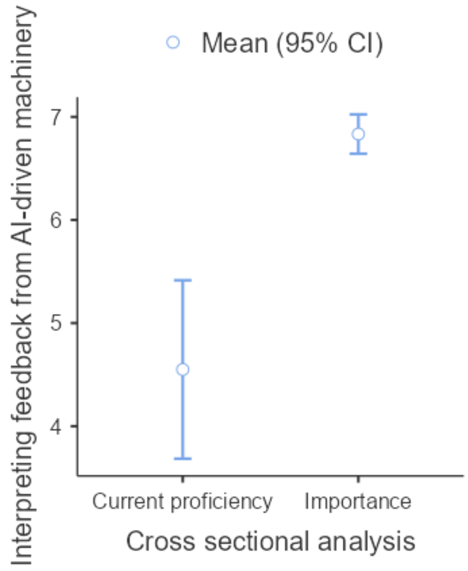

Figure 9

As shown in the table 10 and Figure 9, The cross-sectional analysis of interpreting feedback from AI-driven machinery in developed countries highlights a noticeable gap between worker's current proficiency levels and the perceived importance of this skill**.** The data shows that worker's proficiency in interpreting AI-generated feedback has an average mean of 4.55, while the importance of this skill is rated significantly higher at 6.83. This suggests that while workers demonstrate a **moderate level** of competency in this area, managers still perceive a considerable gap between current skills and what is required for effective AI-driven manufacturing.

The graph visually represents this difference, as the data points for proficiency and importance are clearly separated, with importance positioned much higher. The confidence intervals for importance are very narrow, indicating strong agreement among managers regarding the necessity of this skill. In contrast, the confidence interval for proficiency is wider, suggesting greater variability in worker's ability to interpret AI feedback. This indicates that some workers are more skilled in this area than others, leading to inconsistencies in workforce capability.

A closer look at the standard deviations further supports this interpretation. The standard deviation for proficiency (1.849) is much higher than for importance (0.383), meaning that there is a wider category of skill levels among workers, with some performing well while others lack competency. The low standard deviation for importance shows that managers consistently view this skill as highly necessary.

These findings indicate that while factory workers in developed countries have a moderate ability to interpret AI-generated feedback, their proficiency is not yet aligned with AI-driven manufacturing deemed importance level.

III. **Cross-sectional analysis on operating AI-driven cobot Skills:** In Figure 10, the graph compares the responses of **S1Q13** ("Our factory workers can effectively operate and work alongside AI-driven collaborative robots (cobots)") and **S3Q8** ("Operating AI-driven collaborative robots (cobots) is an important skill for our factory Worker's) to evaluate whether the perceived importance of this skill aligns with the actual proficiency of factory workers or not.

Group Descriptives

	Cross sectional analysis	N	Mean	SD	SE
Operating AI-driven collaborative robots	**Current proficiency** (Section 1)	20	4.40	1.64	0.366
	Importance (Section 3)	20	5.00	2.06	0.485

Table 11

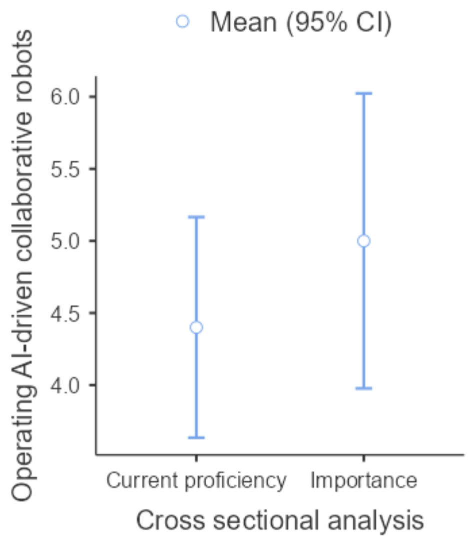

Figure 10

As shown in the table 11 and Figure 10, the cross-sectional analysis of operating AI-driven collaborative robots (cobots) in developed countries shows a relatively **small gap** between worker's current proficiency levels and the perceived importance of this skill. The data indicates that worker's proficiency in operating cobots has an average mean of 4.40, while the importance of this skill is rated at 5.00. On a 1 to 7 scale, where 7 represents the highest level, this suggests that workers have a moderate level of proficiency in cobot operation, and managers perceive this skill as only **moderately important**.

The graph visually represents this relationship, as the data points for proficiency and importance are relatively close, with some overlap in their confidence intervals. This suggests that while managers see cobot operation as somewhat necessary, they do not view it as a top priority compared to other AI-driven skills. The confidence intervals for importance are wider than those for proficiency, indicating greater variation in how managers perceive the necessity of this skill. Some may see it as essential for their operations, while others may not consider it highly relevant.

A closer look at the standard deviations further highlights these differences. The standard deviation for importance (2.06) is noticeably higher than for proficiency (1.64), meaning that opinions on the relevance of cobot operation vary more widely among managers than the actual skill levels among workers. This suggests that while workers exhibit some variation in their ability to operate cobots, there is no strong consensus among managers about whether this skill is crucial in AI-driven manufacturing environments.

These findings indicate that factory workers in developed countries possess a moderate level of skill in operating AI-driven cobots, and managers generally do not see this as a critical gap that requires urgent attention. However, the variability in importance mean s suggests that cobot operation may be more relevant in some workplaces than others, depending on the specific industry or level of automation in different companies.

Cross-Sectional analysis of Skill Gaps and Skill Importance in AI-driven Manufacturing: Sections 2 and 3

In Section 2, a higher mean for certain questions indicates a greater skill gap, while for others, it suggests a lower skill gap.

A higher mean in S2Q1 (Operating AI-driven machinery), S2Q2 (Maintaining automated robotic systems), S2Q3 (Independently maintaining and troubleshooting AI-driven machinery), S2Q4 (Using AI-driven tools for issue resolution), S2Q5 (Working collaboratively with AI-driven machinery), S2Q7 (Using AI-driven quality control systems), S2Q8 (Adjusting and inputting parameters in AI-driven machinery), and S2Q11 (Opportunities and resources for continuous AI learning) indicates **a higher skill gap** in these areas. Where as, a higher mean in S2Q6 (Optimizing AI-driven machinery), S2Q9 (Collaborating with AI-driven cobots), and S2Q10 (Responding positively to AI technologies) suggests that managers perceive a **lower skill gap** in these areas, meaning that workers demonstrate better competency.

This analysis provides a comparison between the severity of skill gaps (measured in Section 2) and the level of importance assigned to these skills (measured in Section 3).

I. **Cross-sectional analysis: Operating AI-driven Machinery Skills:** Figure 11 compares responses to **S2Q1** ("A noticeable gap exists between our factory Worker's current skills and the skills required to operate AI-driven automated robotic systems") and **S3Q1** ("Proficiency in operating AI-driven machinery is an important skill for our factory Worker's).

Group Descriptives

	Cross sectional analysis	N	Mean	SD	SE
Operating AI-driven machinery	**Skill Gap** **(Section 2)**	20	4.90	1.744	0.390
	Importance **(Section 3)**	20	6.89	0.471	0.111

Table 12

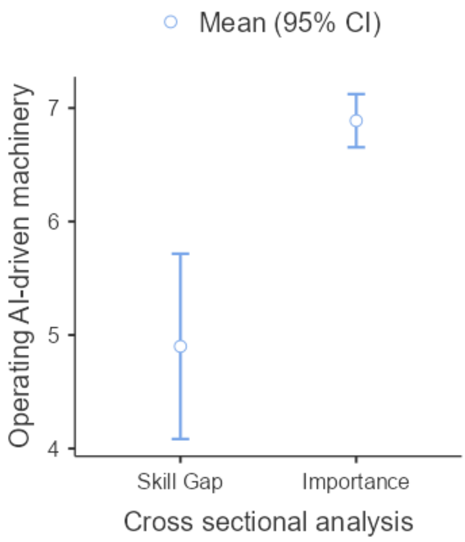

Figure 11

As shown in the table 12 & Figure 11, The cross-sectional analysis of operating AI-driven machinery in developed countries reveals a **moderate skill gap** when assessed in relation to other AI-related skills. The mean of the skill gap is 4.90, this places this skill in the moderate category, meaning workers exhibit some level of deficiency but are not entirely unprepared. However, the importance of this skill is rated significantly higher at 6.89, suggesting that while the gap is not the most severe, it remains a notable concern for managers.

The graph visually reflects this pattern, as the data points for skill gap and importance are separated, with importance positioned higher. The confidence intervals do not overlap, indicating a statistically distinct gap between skill gap and required proficiency. Compared to other AI-related skills, the skill gap for operating AI-driven machinery is not among the highest but is still substantial enough leaving space for improvement.

The standard deviation for skill gap (1.744) is noticeably higher than for importance (0.471), indicating that while managers largely agree on the necessity of this skill, the perceived gap varies across different workplaces. This suggests that some factories may have workers who are relatively competent, while others face more pronounced challenges in AI-driven machinery operation.

When assessed against other AI-related skills in the dataset, the gap in operating AI-driven machinery is not the most critical but is still significant enough to highlight a need for improvement.

Unlike skills such as AI troubleshooting or adjusting AI parameters, where workers exhibit severe gaps, this skill shows a more balanced gap.

II. **Cross-sectional analysis on operating AI-driven Cobots:** The graph in the Figure 12 compares responses to **S2Q5** ("Our factory workers need to improve their skills to work collaboratively with AI-driven machinery") and **S3Q8** ("Operating AI-driven collaborative robots (cobots) is an important skill for our factory workers.

Group Descriptives

	Cross sectional analysis	N	Mean	SD	SE
Operating AI-driven cobots	**Skill Gap** **(Section 2)**	20	5.20	1.36	0.304
	Importance **(Section 3)**	20	5.00	2.06	0.485

Table 13

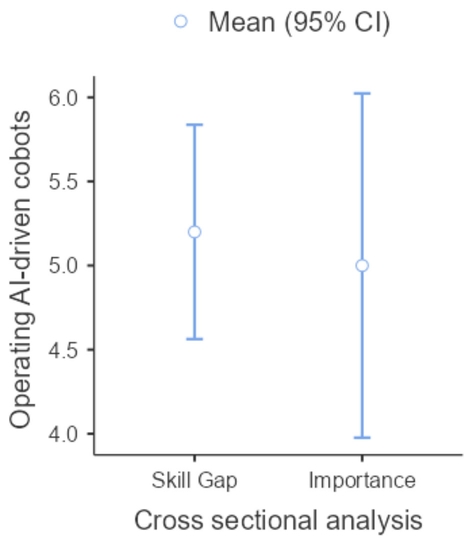

Figure 19

As shown in the Table 13 & Figure 12, The cross-sectional analysis of operating AI-driven collaborative robots (cobots) in developed countries shows that the skill gap and the perceived importance of this skill **are nearly identical.** The data indicates that the skill gap has an average mean of 5.20, while the importance of this skill is rated at 5.00. This suggests that managers recognize a moderate deficiency in worker's ability to collaborate with AI-driven cobots, but they do not universally view this skill as highly critical for factory operations.

The graph visually reflects this alignment, as the data points for skill gap and importance are closely positioned, with overlapping confidence intervals. This suggests that the difference between skill levels and AI-driven manufacturing deemed importance level is not as pronounced compared to other AI-related skills. The wider confidence interval for importance indicates greater variation in how different managers perceive the necessity of this skill, whereas the narrower confidence interval for skill gap suggests that most managers consistently acknowledge the need for improvement in this area.

A closer look at the standard deviations further highlights these differences. The standard deviation for importance (2.06) is significantly higher than for the skill gap (1.36), indicating that while most managers agree that workers need to improve their ability to work with cobots, opinions vary on how crucial this skill actually is. This variation suggests that some manufacturing environments rely heavily on cobots, while others do not prioritize their operation as an essential workforce skill.

When assessed against other AI-related skills in the dataset, the skill gap for operating AI-driven cobots is moderate, neither among the most severe gaps nor among the least concerning. The nearly identical mean s for skill gap and importance suggest that while there is room for improvement, the urgency of addressing this gap may depend on specific industry needs.

III. **Cross-sectional analysis: Adjusting Parameters in AI-driven Machinery:** The graph in Figure 13 compares responses to **S2Q8** ("Our factory workers lack proficiency in adjusting and inputting parameters in AI-driven machinery") and **S3Q9** ("Entering and adjusting data inputs for AI-driven machinery, such as parameters, sensor settings, or performance metrics, is an important skill for our factory Worker's).

Group Descriptives

	Cross sectional analysis	N	Mean	SD	SE
Adjusting parameters in AI-driven machinery	**Skill Gap**	20	4.95	1.96	0.438
	Importance	20	5.30	1.50	0.362

Table 14

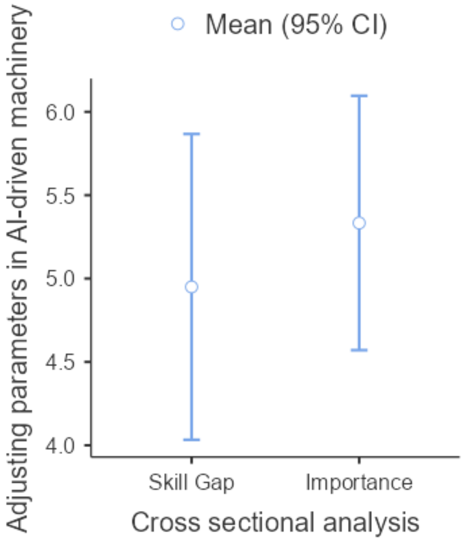

Figure 13

As shown in the Table 14 & Figure 13, The cross-sectional analysis of adjusting parameters in AI-driven machinery in developed countries reveals a **moderate skill gap**, with the skill gap mean averaging 4.95, while the importance of this skill is rated slightly higher at 5.30. In this case since a higher skill gap mean indicates a greater deficiency rather than proficiency, this suggests that while workers struggle with adjusting AI-driven machinery parameters, managers do not view this skill as among the most critical skills in AI-integrated manufacturing.

The graph visually illustrates this alignment, as the data points for skill gap and importance are closely positioned, with overlapping confidence intervals. This indicates that while there is a recognized gap, it is not as severe or pressing as some other AI-related skills. The wider confidence intervals for both measures suggest variability in responses, meaning that some workplaces may see greater challenges in AI parameter adjustments than others.

A closer look at the standard deviations highlights this variability further. The standard deviation for skill gap (1.96) is slightly higher than for importance (1.50), showing that while most managers agree that workers lack proficiency in AI parameter adjustments, the severity of this deficiency differs across different manufacturing environment. Some factories may experience significant challenges in AI configuration, while others may have workers who are more capable in this area.

When compared to other AI-related skills in the dataset, the skill gap for adjusting parameters in AI-driven machinery falls within the moderate category. The similarity in mean s suggests that while workers are not fully proficient, managers do not necessarily see this as a top-priority issue requiring immediate intervention. This implies that upskilling efforts in this area may be beneficial for factories that heavily rely on AI parameter adjustments but may not be an urgent need across all industries.

Cross sectional analysis of Section 1 and 2

This section examines how manager's perceptions in developed countries shift when evaluating the same AI-related skills from two different perspectives. Section 1 focuses on assessing the proficiency levels of factory workers, while Section 2 measures the skill gaps for those exact same skills. By comparing these two sections, we can determine whether managers perceive skill gaps as proportional to proficiency levels or if their responses indicate a stronger sense of urgency for certain skills when framed as a gap rather than a proficiency rating. This distinction is important because it reveals whether managers rate skill gaps more severely than implied by proficiency levels, which could influence training priorities and workforce development strategies. Additionally, this comparison helps identify whether some AI-related skills are seen as more operationally critical, leading to greater discrepancies between proficiency and skill gap assessments. Understanding these patterns is particularly valuable in comparing developed and underdeveloped countries, where workforce readiness and AI adoption challenges may differ significantly.

The analysis compares the following **three skills** across **Section 1 and Section 2**, ensuring that the exact same competency is assessed in both sections:

1. **Maintaining AI-driven machinery** (**S1Q5** vs. **S2Q3**)
2. **Using AI-driven quality control systems** (**S1Q10** vs. **S2Q7**)
3. **Collaborating with AI-driven cobots** (**S1Q13** vs. **S2Q9**)

Difference in responses for same question in section 1 and 2:

S. No	Skills	Proficiency level	Skill gap
1	Maintaining AI-driven machinery	3.0	6.5
2	Using AI-driven quality control systems	4.05	4.3
3	Collaborating with AI-driven cobots	4.4	4.65

Table 15

As shown in the table 15, that managers in developed countries rated skill gaps higher than what Section 1 proficiency levels suggest, particularly for AI maintenance.

1. For **maintaining AI-driven machinery**, workers have low proficiency, with a mean 3.0, meaning they lack proficiency in this skill. Proficiency is directly linked to skill gaps, the implied gap should have been 4.0 (The maximum value in the likert scale minus the mean of the skill, 7 – 3 = 4). However, in Section 2, managers rate the skill gap at 6.5, **significantly higher than expected**. This suggests that AI maintenance is considered a high-priority gap, where managers perceive worker's inability to perform maintenance as a severe operational limitation rather than just a skill gap.

2. For using **AI-driven quality control systems**, workers exhibit moderate proficiency at 4.05, indicating a **moderate competency level**. This suggests that, based on their observations, workers possess some familiarity with AI-driven quality control but are not fully skilled. If proficiency ratings directly translated to skill gaps, the implied gap would be 2.95 (The maximum value in the likert scale minus the mean of the skill, 7 - 4.05). However, the mean skill gap rating given by managers in Section

2 is 4.3, which is **higher than expected**. This suggests that while managers acknowledge some level of competency among workers, they still perceive a greater gap than what Section 1 proficiency scores suggest, reinforcing the idea that worker's current abilities are insufficient to fully meet the demands of AI-integrated manufacturing. **Interestingly**, this creates an **indirect contradiction** in the manager's responses. This inconsistency highlights that managers may be perceiving gaps more critically when framed as a gap rather than when assessing proficiency directly, potentially influencing how training needs are prioritized.

3. While assessing **collaborating with AI-driven cobots**, workers exhibit moderate proficiency at 4.4, indicating a **moderate competency level**. This suggests that, based on their observations, workers have some ability to work alongside AI-driven collaborative robots but are not fully proficient. If proficiency ratings directly translated to skill gaps, the implied gap would be 2.6 (The maximum value in the likert scale minus the mean of the skill, 7 - 4.4). However, the mean skill gap rating given by managers in Section 2 is 4.65, which is **higher than expected**. This suggests that while managers acknowledge that workers have some competency in working with cobots, they still perceive a greater gap than what Section 1 proficiency scores suggest, implying that worker's current abilities are not fully aligned with AI-integrated production expectations. Interestingly, this creates an indirect contradiction in the manager's responses. This inconsistency highlights that managers may be perceiving gaps more critically when framed as a gap rather than when assessing proficiency directly, potentially influencing how training needs are prioritized.

5.2.1.4 Findings from the analysis of developed countries:

Analysis of Section 1 (Proficiency level), 2 (Skill Gap) and 3 (Importance of the skill):

The findings from Section 1 highlight varying levels of proficiency among factory workers in AI-driven manufacturing environments. Workers demonstrate **high proficiency in only one area** that is 'participation in AI training programs' indicating strong engagement in continuous learning. However, this is not a skill but rather an indication of worker's willingness to develop their competencies. Most AI-related skills fall within the **moderate proficiency level**, suggesting that while workers exhibit some capability in operating AI-driven machinery, adapting to AI technologies, and interpreting AI-generated feedback, their abilities remain below the proficient level. Their familiarity with predictive maintenance, quality control systems, and collaborative work with AI-driven robots also shows competency but not proficiency. Despite this moderate familiarity, workers lack proficiency in maintaining and adjusting AI-driven machinery, as well as in using AI-based production planning tools. This indicates that while they may be capable of operating AI systems, they struggle with technical modifications and optimization. The most **significant concern** is their limited ability to troubleshoot AI-driven machinery, as this skill falls into the significantly lacking category. Without the capability to diagnose or resolve even minor AI malfunctions, factories risk frequent disruptions and operational inefficiencies.

The findings from Section 2 focus on skill gaps among factory workers, revealing that the most significant skill gaps exist in AI maintenance, troubleshooting, training, and continuous learning opportunities. The severe gap in continuous learning suggests that workers need better training initiatives and resources to keep pace with AI advancements, further limiting their ability to adapt to evolving technologies. A moderate skill gap is observed in operating and maintaining AI robotic systems, working collaboratively with AI-driven machinery, adjusting AI parameters, and using AI-driven quality control systems. While workers have some exposure to these technologies, their ability to fine-tune, optimize, and interact effectively with AI remains limited. Interestingly, the assessment of worker's ability to optimize AI-driven machinery shows mixed results, suggesting that while some adjustments are possible, effectiveness varies among workers. Notably, no skill gaps were rated 1 on a 1 to 7 likert scale indicating a complete absence of ability, meaning **workers possess at least a foundational understanding of all AI-related tasks**. However, the combination of high and moderate skill gaps indicates a clear need for upskilling initiatives. Without addressing these skill gaps, manufacturing plants will continue to rely on external technical support for AI maintenance and troubleshooting, leading to increased downtime and inefficiencies.

The findings from Section 3 reveal that factory managers **highly prioritize three key skills** for AI-driven manufacturing: proficiency in operating AI-driven machinery, understanding and responding to AI-generated alerts, and the ability to quickly learn and adapt to new AI-driven technologies. These skills are considered highly important as they directly impact production efficiency, AI system reliability, and workforce adaptability. The emphasis on quick learning suggests that AI-integrated factories require workers who can rapidly adapt to evolving AI technologies, minimizing disruptions and maintaining smooth production processes. Several technical skills fall within the **moderate importance category**, including performing routine AI maintenance, controlling advanced AI robotic systems, interacting with human-machine interfaces, and managing AI-based quality control systems. While these skills are necessary, they are not considered as critical as direct AI machinery operation and real-time AI alert handling. Similarly, the ability to adjust AI machinery parameters, implement AI-specific safety protocols, and operate AI-driven collaborative robots is seen as useful but not as urgent as core operational skills.

Only one skill is regarded as **less important** that is 'proficiency in using machine learning algorithms', this suggests that managers do not expect factory workers to develop or modify AI algorithms but instead focus on practical AI operation and system interaction. Overall, the findings reinforce that AI-driven manufacturing prioritizes hands-on AI proficiency, real-time problem-solving, and adaptability, rather than deep technical AI development.

Cross-sectional analysis:

The cross-sectional analysis comparing skill proficiency (Section 1) and skill importance (Section 3) in developed countries highlights clear discrepancies between worker's current abilities and managerial deemed importance level in AI-driven manufacturing.

Findings from operating AI-driven machinery reveal that workers demonstrate a moderate level of proficiency, but managers consider this skill highly important. The graph shows a significant gap, with importance rated much higher than proficiency, suggesting that **current skill levels are not sufficient** to meet industry demands. While workers exhibit some ability in operating AI-driven machinery, their competencies remain below the deemed importance level for AI-integrated manufacturing environments. Most managers agree on the importance of this skill, but there is variation in how proficient they perceive workers to be, indicating **inconsistencies in skill levels across different factories.**

A similar trend is observed in interpreting feedback from AI-driven machinery. Workers have a **moderate level** of ability in understanding AI-generated feedback, but managers overwhelmingly consider this skill essential. The graph highlights a clear difference, with the importance mean being much higher than proficiency, indicating that workers struggle with interpreting and responding to AI-generated alerts. Most managers agree on the necessity of this skill, but responses regarding worker proficiency vary, suggesting that while some workers may have basic competency, others lack sufficient understanding. This inconsistency in proficiency reinforces the need for upskilling to improve AI feedback interpretation and real-time response capabilities.

Findings on operating AI-driven collaborative robots (cobots) show a relatively **small gap** between proficiency and importance. The graph indicates that worker's skill levels and deemed importance level are more aligned compared to other AI-related competencies. While some managers see cobot operation as essential, others do not view it as a priority, leading to greater variation in how important this skill is perceived to be. Worker proficiency also varies across different workplaces, suggesting that **some factories have integrated cobots more effectively into their operations, while others may not rely on them as heavily.**

The cross-sectional analysis comparing skill gaps (Section 2) and skill importance (Section 3) further highlights key areas requiring workforce upskilling.

Findings from operating AI-driven machinery indicate a moderate skill gap, while managers consider this skill highly important. The graph shows a clear separation between the skill gap and the importance mean , reinforcing that while **workers are not entirely unprepared**, yet their current competencies still fall short of deemed importance level of the skill. Most managers agree on the importance of this skill, but there is some variation in how severe they perceive the gap to be, suggesting differences in AI adoption and worker training across manufacturing industry.

Findings from operating AI-driven collaborative robots (cobots) indicate that the **skill gap and perceived importance are nearly identical**. The graph suggests that managers and workers are largely aligned in their assessment of cobot-related skills, with no significant gap between deemed importance level and current capabilities. However, **not all managers agree on the importance of cobot operation**, as responses vary widely, indicating that its relevance depends on specific industry needs and production processes.

Findings from adjusting parameters in AI-driven machinery indicate a moderate skill gap, with managers rating this skill slightly higher in importance. The graph shows that while workers struggle with AI parameter adjustments, this gap is not as severe as others in the dataset. **Some managers consider parameter adjustment a crucial skill, while others do not view it as highly necessary**, leading to differences in how urgent this gap appears across manufacturing environment. Worker proficiency also varies, suggesting that **some workers have basic familiarity with AI adjustments, while others lack the skill entirely**.

Overall, these findings highlight significant gaps in AI-driven machinery operation and AI feedback interpretation, both of which are seen as highly important yet remain areas where workers lack sufficient expertise. Meanwhile, skills such as cobot operation and AI parameter adjustments show a more balanced relationship between skill gaps and importance, suggesting they are less of an immediate concern. While most managers agree on the critical skills needed in AI-driven manufacturing, there is some variation in how they perceive worker proficiency and the severity of skill gaps, indicating differences in AI adoption and training opportunities across companies.

Cross sectional analysis of section 1 (Proficiency level) and section 2 (Skill gap)

The Cross-sectional analysis between worker proficiency level and perceived skill gaps reveals notable difference in how managers in the developed countries assess AI-related competencies when the same question is asked differently. **For maintaining AI-driven machinery**, workers are rated as lacking proficiency, yet managers perceive the skill gap as significantly higher than what the proficiency score suggests. This indicates that AI maintenance is viewed not just as a deficiency but as a critical operational challenge. **For using AI-driven quality control systems**, workers demonstrate moderate competency, yet managers rate the skill gap higher than expected, suggesting that even though workers have some familiarity, their capabilities are still seen as insufficient for AI-integrated manufacturing. This discrepancy highlights an **indirect contradiction** in managerial responses, as their skill gap ratings reflect a stronger concern than their proficiency assessments imply. **For collaborating with AI-driven cobots**, workers also exhibit moderate proficiency, but managers still perceive a greater need for improvement than what proficiency scores alone indicate. These inconsistencies suggest that when asked about proficiency, managers provide a more neutral evaluation, but when the same skill is framed as a gap, they perceive it more critically. This pattern could influence how training needs are prioritized, potentially leading to a stronger emphasis on upskilling in areas where perceived gaps are more pronounced.

5.2.3 Analysis of Underdeveloped countries:

The analysis for underdeveloped countries focuses on the 30 respondents of underdeveloped countries within the total dataset of 50, collected through surveys, starting with the analysis of Section 1 (worker's proficiency level of the skills), Section 2 (skill gaps), and Section 3 (deemed importance of the skills by managers), and then conducting a cross-sectional analysis to compare proficiency levels with skill importance, as well as skill gaps with skill importance. Each of these analyses serves a distinct purpose in understanding workforce readiness for AI-driven manufacturing.

The analysis of Section 1 provides insight into which skills workers demonstrate high proficiency in, which skills they are moderately proficient in, and which skills they significantly lack. However, knowing proficiency alone does not indicate whether workers meet industry expectations. To address this, Section 2 examines skill gaps separately, measuring the extent to which workers lack essential AI-related abilities. A skill could have moderate proficiency yet still present a gap if workers are not performing at the level required by AI-driven manufacturing. Similarly, a skill with low proficiency may not necessarily be a priority if it is not critical to production processes. Beyond assessing skill levels and gaps, Section 3 evaluates which AI-related skills managers consider the most important. Some skills may be highly proficient yet not prioritized by managers, while others may have large skill gaps but are not seen as essential. Understanding skill importance ensures that workforce training efforts are aligned with industry needs and AI integration strategies.

5.2.2.2 Sectional analysis

Section 1:

Figure 14 illustrates the average responses to survey questions in section 1, addressing the skills and abilities of factory workers in AI-driven manufacturing environments. The responses are based on a Likert scale ranging from **1 (strongly disagree)** to **7** (**strongly agree**). The data reflects varying levels of agreement with the statements provided in the survey, highlighting proficiency of skills in factory workers.

In the graph (Figure 14) Skills with a mean between 6 and 7 are classified as **'proficient'** represented by green-coloured bars, skills with a mean between 4 and 6 indicate a **'moderate proficiency'** represented by yellow-coloured bars, skills with a mean between 3 and 4 are categorized as **'lacking proficiency'** represented by category-coloured bars, and skills with a mean below 3 are classified as **'significantly lacking the skill'** represented by red coloured bars.

Additionally, the numerical value in the brackets next to the name of the skills are the mean values of those skills.

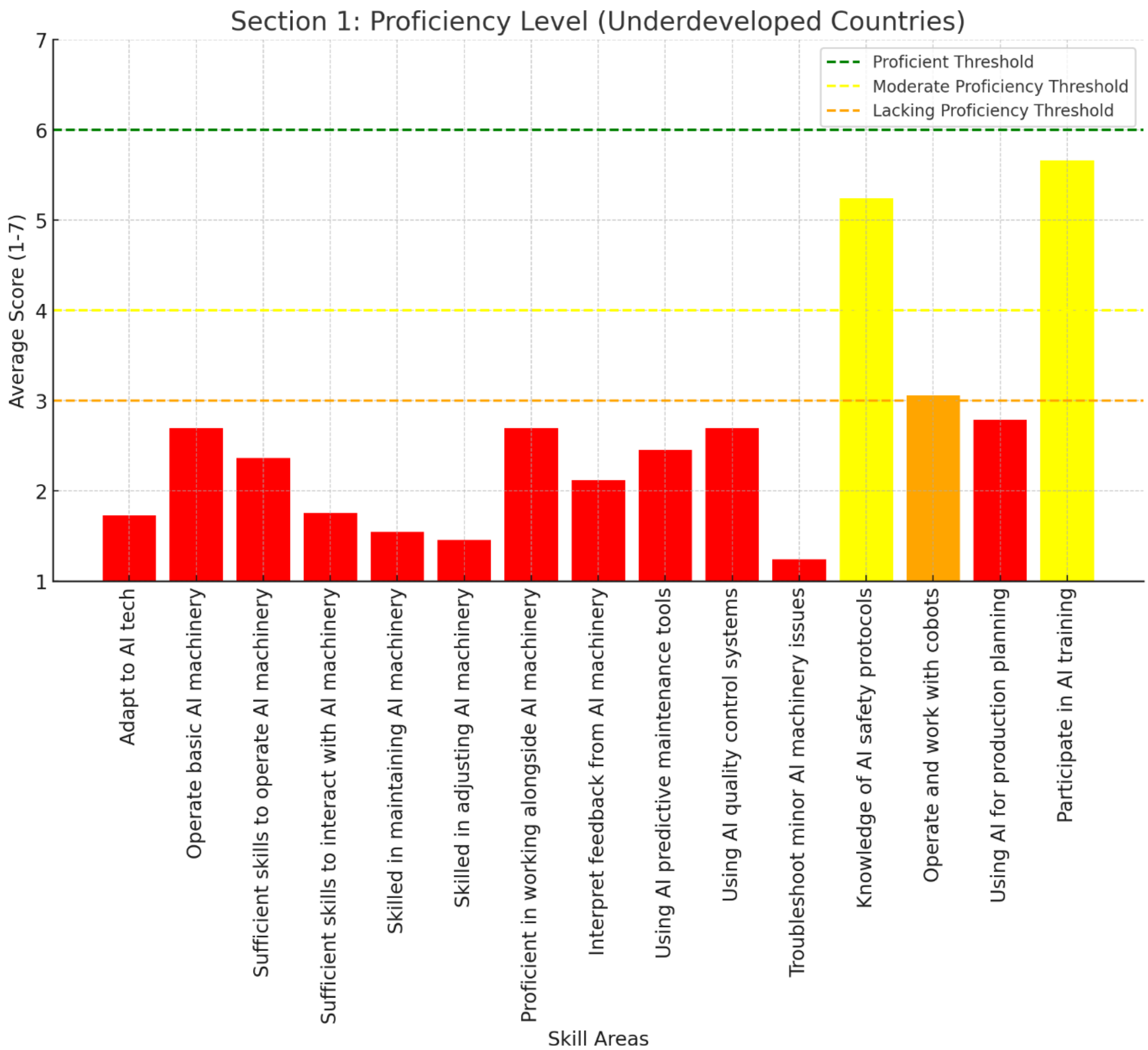

Figure 14

Factory workers in underdeveloped countries do not demonstrate proficiency in any AI-related skills. Only two skills fall within the moderate proficiency category, and they are **'knowledge of AI safety**

protocols' (5.24) and **'participation in AI training'** (5.67). This suggests that while workers receive some level of training and are aware of safety measures, however these are not skills. The presence of training does not necessarily indicate skill proficiency, and the lack of proficiency across all other AI-related areas suggests that current training initiatives may not be sufficiently practical or application-based.

Most core AI operational skills are **severely lacking**, indicating that while workers may have some exposure to these skills, their ability to apply them in real-world AI-driven environments is highly insufficient. These include adapting to AI technology (1.73), operating basic AI machinery (2.70), interacting with AI-driven machinery (1.76), maintaining AI-driven machinery (1.54), and troubleshooting AI machinery issues (1.24). These low mean s suggest that workers are largely unprepared for AI-integrated manufacturing, requiring significant training and skill development before they can effectively engage with AI-driven processes. Additionally, working with cobots (3.06) falls in the lacking proficiency category, indicating that while some workers may have minimal experience with AI-driven collaborative robots, their ability to use them efficiently remains inadequate.

Overall, the data highlights **a severe** skill gap in AI readiness among factory workers in underdeveloped countries. The fact that **only two skills fall in the moderate proficiency category** while the majority are severely lacking suggests that workers are not adequately prepared for AI-driven manufacturing. As of now the companies may focus more on theoretical knowledge rather than hands-on skill-building, as workers seem to understand safety protocols but lack the ability to operate AI-driven machinery independently.

Section 2:
The Figure 15 that represents Section 2, a higher mean for certain questions indicates a greater skill gap, while for others, it suggests a lower skill gap.

A higher mean in S2Q1 (Operating AI-driven machinery), S2Q2 (Maintaining automated robotic systems), S2Q3 (Independently maintaining and troubleshooting AI-driven machinery), S2Q4 (Using AI-driven tools for issue resolution), S2Q5 (Working collaboratively with AI-driven machinery), S2Q7 (Using AI-driven quality control systems), S2Q8 (Adjusting and inputting parameters in AI-driven machinery), and S2Q11 (Opportunities and resources for continuous AI learning) indicates **a higher skill gap** in these areas. Where as, a higher mean in S2Q6 (Optimizing AI-driven machinery), S2Q9 (Collaborating with AI-driven cobots), and S2Q10 (Responding positively to AI technologies) suggests that managers perceive a **lower skill gap** in these areas, meaning that workers demonstrate better competency.

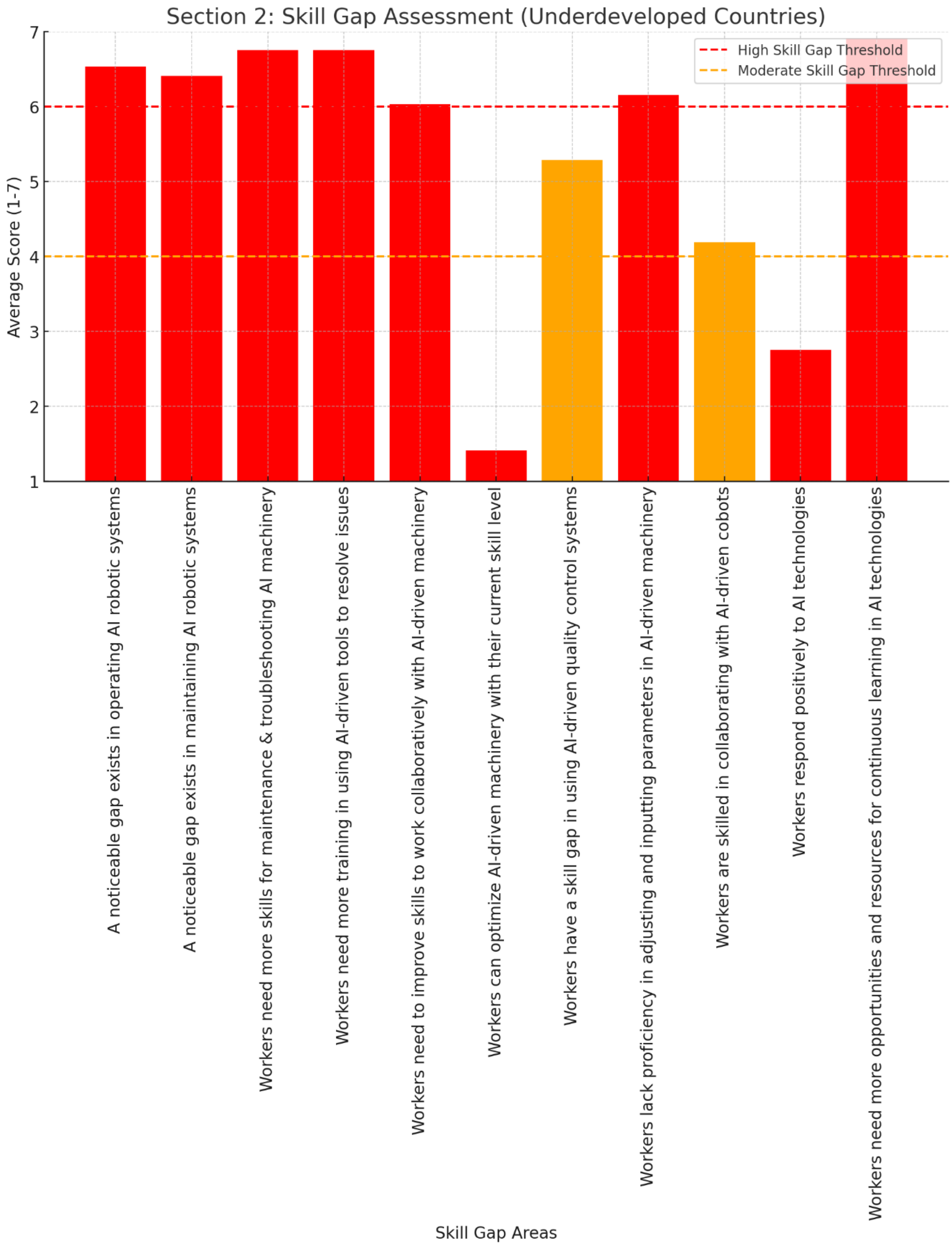

Figure 15

Factory workers in underdeveloped countries exhibit **high skill gaps** in nearly all critical AI-related areas, particularly in operating (6.50) and maintaining AI robotic systems (6.41), performing maintenance and troubleshooting (6.75), using AI-driven tools for issue resolution (6.75), and improving collaboration with AI-driven machinery (6.03). Additionally, the highest skill gap (6.91) is in accessing continuous learning opportunities in AI technologies, indicating that workers not only lack AI-related skills but also have insufficient access to training programs that could help bridge these gaps. These findings suggest that AI-driven factories in underdeveloped regions lack a skilled workforce capable of operating and maintaining AI-integrated manufacturing processes, creating a major barrier to AI adoption and efficiency.

A **moderate skill gap** is observed in using AI-driven quality control systems (5.28) and collaborating with AI-driven cobots (4.19), suggesting that workers have some exposure to these technologies but lack the necessary expertise to use them effectively. However, these gaps remain significant enough to hinder operational efficiency, as AI-driven quality control is a critical component of modern manufacturing.

One notable anomaly is the significantly lower mean (1.41) for optimizing AI-driven machinery, indicating that workers in underdeveloped countries are almost entirely unable to adjust, fine-tune, or optimize AI-driven processes. Additionally, their response to AI technologies (2.75) is categorized as a significantly low skill gap, suggesting that while workers may not reject AI adoption, they lack the necessary training and knowledge to integrate it effectively into their workflow.

Overall, the data highlights a severe lack of AI-related skills among factory workers in underdeveloped countries, particularly in machine operation, troubleshooting, and optimization. The absence of continuous learning opportunities (6.91) further worsens the situation, preventing workers from gaining the necessary expertise to operate AI-driven systems effectively, questioning the intention of the companies towards AI-driven manufacturing.

Section 3:
In Figure 16, The section 3 evaluates the importance of various AI-related skills required for factory workers in underdeveloped regions to effectively operate, maintain, and optimize AI-driven machinery in an AI-driven manufacturing environment.

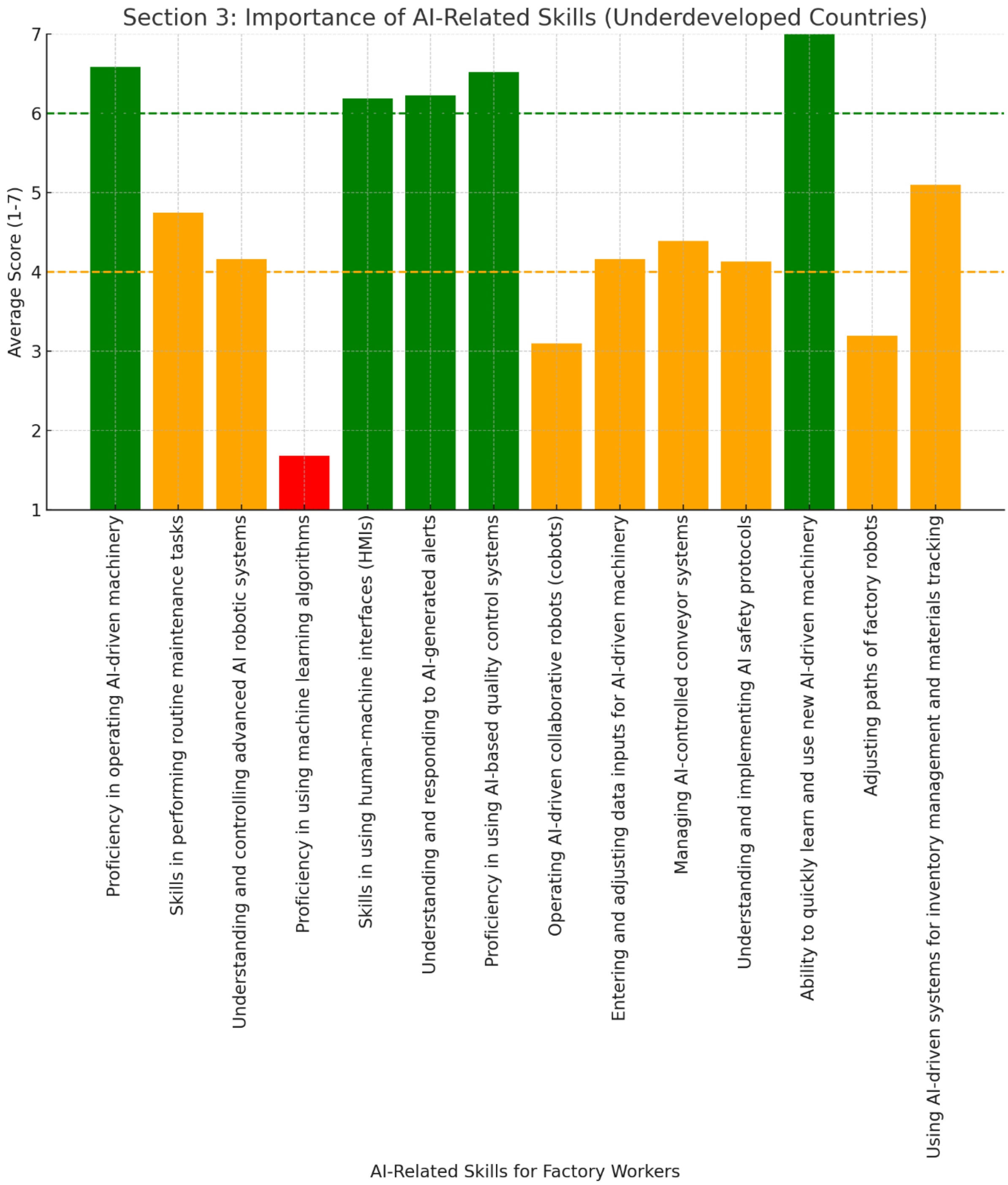

Figure 16

Factory managers in underdeveloped countries identified the ability to quickly learn and use new AI-driven machinery (7.00) as the **most critical skill** for factory workers. This highlights the necessity for workers to rapidly adapt to AI advancements and integrate new technologies into their daily tasks. Other highly important skills include proficiency in operating AI-driven machinery (6.58), understanding and responding to AI-generated alerts (6.23), and proficiency in using AI-based quality control systems (6.52). The emphasis on AI alerts and quality control suggests that factories require workers who can monitor AI-assisted processes in real time and ensure consistent production quality through automated inspection systems.

Several skills were considered **moderately important**, including performing routine maintenance tasks (4.74), understanding and controlling advanced AI robotic systems (4.16), entering and adjusting data inputs for AI-driven machinery (4.16), and managing AI-controlled conveyor systems (4.39). These findings indicate that while technical interaction with AI-driven systems is necessary, it is not as critical as direct operation and rapid adaptability. Understanding and implementing AI safety protocols (4.13) also falls within this category, suggesting that while safety is a factor, the primary focus remains on efficiency and operational integration of AI.

A few skills were considered **less important**, including proficiency in using machine learning algorithms (1.68), operating AI-driven collaborative robots (3.10), and adjusting paths of factory robots (3.19). The particularly low emphasis on machine learning algorithms indicates that factory managers do not expect workers to develop or modify AI systems, reinforcing the idea that their role is to operate and interact with AI rather than engage in its technical design.

Overall, the findings indicate that workers in underdeveloped countries must focus on quickly adapting to AI technologies, efficiently operating AI-driven machinery, and ensuring smooth production workflows through AI-assisted monitoring and quality control. While some level of technical interaction with AI is necessary, complex AI programming and robotic adjustments are not seen as essential responsibilities for factory workers.

5.2.2.3 Cross-Sectional analysis:

This section presents a cross-sectional analysis between Sections 1 and 3, focusing on the alignment between factory Worker's current skills (Section 1) and the skills identified as important for workers to learn (Section 3). By comparing responses to similar questions from both sections, this analysis aims to identify overlaps, gaps, and priorities in skill development for AI-driven manufacturing environments. The analysis highlights areas where the workforce's existing proficiency aligns with or falls short of the perceived importance of specific skills, as assessed by the respondents. In the figures below, "S" represents the section and "Q" is the question number. Example: S3Q1 represents question 1 from section 3.

Table description: In cross-sectional analysis, the sample size (N) represents the total number of respondents in the underdeveloped countries data set. This indicates how many managers provided responses for a particular skill assessment. For example, if N = 30, it means that the responses from 30 managers (the data set of underdeveloped countries) were considered when calculating the skill gap, proficiency levels, or skill importance. A larger N generally results in more stable and reliable estimates, as it reflects a broader perspective from industry professionals.

The mean represents the average of all responses for a particular skill, skill gap, or skill importance. It provides a central value that summarizes the overall trend of responses. For example, if the mean for proficiency in operating AI-driven machinery is 2.70, it indicates that, on average, managers rate their worker's ability at a significantly lacking level. The mean helps compare how different AI-related skills are perceived in terms of importance, proficiency, or skill gaps.

The standard deviation (SD) measures the spread or variability of responses around the mean. A low standard deviation indicates that most responses are clustered closely around the mean, meaning there is a general consensus among respondents. In contrast, a high standard deviation suggests that responses are widely spread, indicating differing opinions among managers. For example, if the SD for proficiency in AI-driven machinery is 1.24, it means that while some managers may rate worker's skills as significantly lacking, others may perceive them slightly better, but overall, responses remain low.

The standard error (SE) reflects how much the mean might vary if the study were repeated with a different sample of managers. It accounts for sampling variability and helps assess the precision of the mean estimate. A lower SE indicates a more reliable mean, suggesting that the responses are more consistent across the sample. For example, if the SE for skill importance is 0.21, it means that the estimated mean is relatively stable and would likely remain close to this value in another study. However, a higher SE (e.g., 0.48) indicates that the mean could fluctuate more if the study were repeated with a different sample.

These statistical measures provide valuable insights into workforce proficiency, skill skill gaps, and the perceived importance of AI-related competencies in underdeveloped countries.

Cross sectional analysis between section 1 and section 3:

I. **Cross-sectional analysis on Operating AI-driven Machinery Skills:** In Figure 17, the graph compares the responses of **S1Q2** ("Our factory workers can effectively operate basic AI-driven machinery without requiring constant supervision") and **S3Q1** ("Proficiency in operating AI-driven machinery is an important skill for our factory Worker's).

Group Descriptives

	Cross sectional analysis	N	Mean	SD	SE
Operating AI-drive machinery	**Current Proficiency**	30	2.70	0.847	0.147
	Importance	30	6.58	1.205	0.216

Table 16

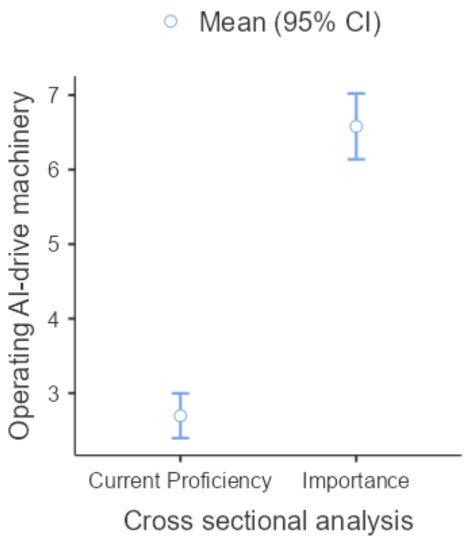

Figure 17

From table 16 & Figure 17, the cross-sectional analysis of operating AI-driven machinery in underdeveloped countries highlights a significant gap between current proficiency levels and how important this skill is considered by managers. The data shows that while managers believe operating AI-driven machinery is **highly important**, with a mean of 6.58, worker's actual proficiency in this area is **significantly lacking** with a mean of 2.70. On a scale of 1 to 7, where 7 represents the highest level, this means that managers overwhelmingly agree that this skill is essential, yet they also recognize that workers lack the necessary expertise.

The graph provides a clear visual representation of this gap. The two data points; one for proficiency and one for importance are positioned far apart, showing that the skill level of workers does not align with what is needed. The vertical bars on each data point, representing 95% confidence intervals, confirm that the difference between proficiency and importance is not just large but also statistically significant, as their confidence intervals do not overlap.

Beyond the numerical gap, the data also reveals another key insight. The importance of this skill shows greater variation among respondents (SD = 1.205) compared to proficiency (SD = 0.847). In other words, while everyone agrees that workers are not very skilled in AI-driven machinery, there is some difference in how strongly managers feel about its importance. However, it doesn't make a difference as operating AI-driven machinery is widely seen as crucial, and current skill levels are far from adequate.

This analysis strongly indicates a need for workforce development programs focused on AI-driven machinery. As AI becomes increasingly integrated into manufacturing, workers must be trained to operate these systems effectively. Without the right skills, factories may face inefficiencies, slower AI adoption, and increased reliance on external technical support.

II. **Cross-sectional analysis on Interpreting Feedback from AI-driven Machinery Skills:** In Figure 18, the graph compares the responses of **S1Q8** ("Our factory workers can interpret feedback from AI-driven machinery”) and **S3Q6** (“Understanding and responding to alerts generated by AI machinery is crucial”).

Group Descriptives

	Cross sectional analysis	N	Mean	SD	SE
Interpreting feedback from AI-driven machinery	**Current Proficiency**	30	2.12	1.24	0.217
	Importance	30	6.68	1.14	0.204

Table 17

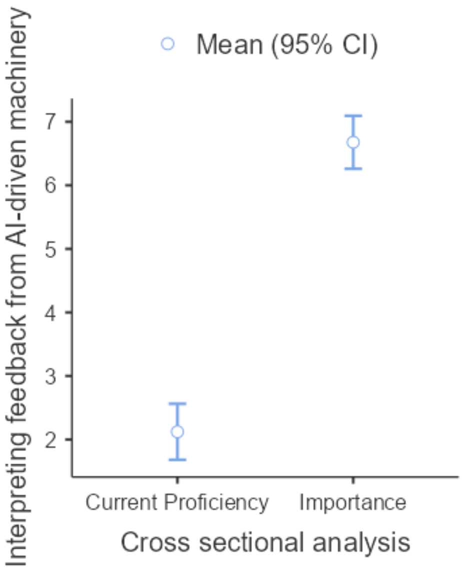

Figure 18

As shown in the Figure 18, The cross-sectional analysis of interpreting feedback from AI-driven machinery in underdeveloped countries highlights a substantial gap between current proficiency levels and how important this skill is considered by managers. The data indicates that while managers regard understanding and responding to AI-generated alerts as **highly important,** with a mean of 6.68, worker’s ability to interpret feedback from AI-driven machinery is **significantly lacking,** with a mean of 2.12.

The graph (Figure 18) clearly shows this gap, as the two data points for proficiency and importance are positioned far apart, visually emphasizing the difference between how necessary this skill is perceived to be and the worker’s current ability to perform it. The confidence intervals for both measures remain distinct, maintaining a visible separation between the two points. This confirms that the difference between proficiency and importance is not only substantial but also consistent across respondents.

A closer look at the standard deviation values provides additional insight into this difference. The standard deviation for proficiency (1.24) indicates that worker’s skill levels vary, but most responses remain low. Similarly, the standard deviation for importance (1.14) suggests that while managers may have slightly different views on how critical this skill is, they largely agree on its high importance. This similarity in variation reinforces the finding that workers consistently struggle with interpreting AI feedback, while managers consistently view it as essential.

These findings highlight a clear difference between deemed importance level and current proficiency in AI feedback interpretation. As AI-driven systems become more integrated into manufacturing, interpreting feedback from AI-driven machinery remains an area where workers exhibit **low proficiency relative to its perceived importance.**

III. **Cross-sectional analysis on Operating AI-driven Cobots Skills:** In Figure 19, the graph compares the responses to **S1Q13** ("Our factory workers can effectively operate and work alongside AI-driven collaborative robots (cobots)") and **S3Q8** ("Operating AI-driven collaborative robots (cobots) is an important skill for our factory Worker's) to evaluate whether the perceived importance of this skill aligns with the actual proficiency of factory workers or not.

Group Descriptives

	Cross sectional analysis	N	Mean	SD	SE
Operating AI-driven Cobots	**Current Proficiency**	30	3.06	1.37	0.238
	Importance	30	3.10	2.31	0.416

Table 18

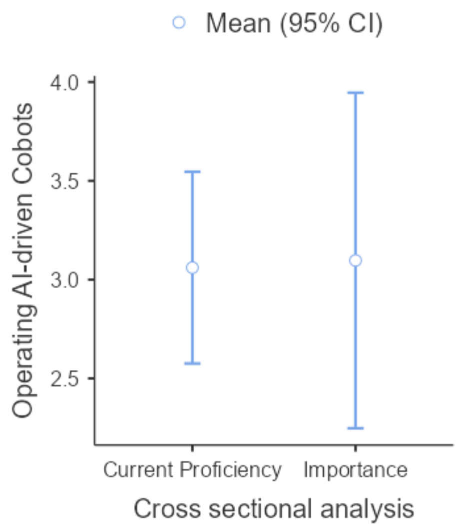

Figure 19

As shown in the Figure 19 and table 18, The cross-sectional analysis of operating AI-driven collaborative robots (cobots) in underdeveloped countries reveals that **current proficiency and perceived importance are nearly identical.** The data shows that worker's proficiency in operating cobots has a mean of 3.06, while managers rate the importance of this skill at 3.10. Unlike previous analyses where importance was significantly higher than proficiency, these two measures are closely aligned, suggesting that **managers do not view cobot operation as a highly critical skill, nor do workers exhibit high proficiency in it.**

The graph visually represents this similarity, as the two data points for proficiency and importance are positioned very close to each other. Additionally, the confidence intervals overlap considerably, which indicates that the small difference between proficiency and importance is not statistically significant. This means that manager's deemed importance level of cobot operation closely match worker's current capabilities, and there is no clear indication that this skill is considered urgent for improvement.

The standard deviation for importance (**2.31**) is much higher than for proficiency (1.37), indicating greater **variability in manager's opinions** about how critical this skill is. While some may see cobot operation as essential, others may not consider it as important. In contrast, the lower standard deviation for proficiency suggests that most workers perform at a similar level when operating cobots. This suggests that there are no extreme variations in skill level, but there is considerable uncertainty in how necessary this skill is perceived to be.

These findings indicate that operating AI-driven cobots is not currently seen as a highly prioritized skill in AI-driven manufacturing. While proficiency remains relatively low, the similar importance rating suggests that there is no widespread concern regarding the need for immediate upskilling in this area. However, the high variability in importance mean s suggests that cobot operation may become more relevant in certain workplaces, depending on specific industry needs.

Cross sectional analysis between section 2 and section 3:

In Section 2, a higher mean for certain questions indicates a greater skill gap, while for others, it suggests a lower skill gap.

A higher mean in S2Q1 (Operating AI-driven machinery), S2Q2 (Maintaining automated robotic systems), S2Q3 (Independently maintaining and troubleshooting AI-driven machinery), S2Q4 (Using AI-driven tools for issue resolution), S2Q5 (Working collaboratively with AI-driven machinery), S2Q7 (Using AI-driven quality control systems), S2Q8 (Adjusting and inputting parameters in AI-driven machinery), and S2Q11 (Opportunities and resources for continuous AI learning) indicates **a higher skill gap** in these areas. Where as, a higher mean in S2Q6 (Optimizing AI-driven machinery), S2Q9 (Collaborating with AI-driven cobots), and S2Q10 (Responding positively to AI technologies) suggests that managers perceive a **lower skill gap** in these areas, meaning that workers demonstrate better competency.

This analysis provides a comparison between the severity of skill gaps (measured in Section 2) and the level of importance assigned to these skills (measured in Section 3).

I. **Cross-sectional analysis on Interpreting Feedback from AI-driven Machinery Skills:** In Figure 20, the graph compares the responses to **S2Q1** ("A noticeable gap exists between our factory Worker's current skills and the skills required to operate AI-driven automated robotic systems") and **S3Q1** ("Proficiency in operating AI-driven machinery is an important skill for our factory Worker's), for **S2Q1** a higher mean value indicates a greater skill gap rather than proficiency.

Group Descriptives

	Cross sectional analysis	N	Mean	SD	SE
Operating AI-driven machinery	**Skill Gap**	30	6.50	0.803	0.142
	Importance	30	6.58	1.205	0.216

Table 19

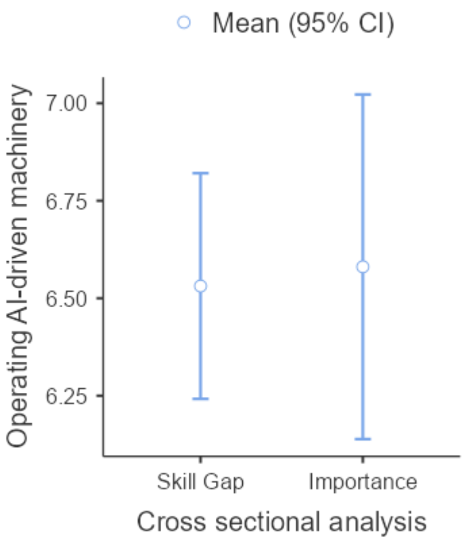

Figure 20

As shown in the Figure 20, The data shows that the skill gap has an average mean of 6.50, while the importance of this skill is slightly higher at 6.58. In this case, a higher mean for the skill gap indicates a greater lack of proficiency rather than competence. The similarity in mean suggests that managers not only view this skill as **highly important** but also acknowledge that the existing workforce **significantly lack** the required proficiency to operate AI-driven machinery effectively.

The graph visually supports this observation, as the two data points for skill gap and importance are positioned very close to each other, indicating that the severity of the skill gap aligns closely with the perceived necessity of AI machinery operation. The confidence intervals also overlap, suggesting that while there may be slight variations in responses, the overall trend remains the same factory workers are widely seen as lacking this skill, and managers consider it essential.

The standard deviation for importance (1.205) is larger than for the skill gap (0.803), indicating that while most managers agree that there is a significant skill gap, there is slightly more variation in how important they consider this skill to be. This suggests that while the lack of proficiency is a widely recognized issue, the urgency of addressing it may differ depending on the specific workplace or industry.

These findings highlight a major workforce deficiency in AI-driven machinery operation, with managers clearly identifying this as a critical gap that needs to be addressed.

II. **Cross-sectional analysis on Operating AI-driven Cobots Skills:** In Figure 21, the graph compares the responses of S2Q5 ("Our factory workers need to improve their skills to work collaboratively with AI-driven machinery") and S3Q8 ("Operating AI-driven collaborative robots (cobots) is an important skill for our factory Worker's), for S2Q5 a higher mean value indicates a greater skill gap rather than proficiency.

Group Descriptives

	Cross sectional analysis	N	Mean	SD	SE
Operating AI-driven Cobots	**Skill Gap**	30	6.03	0.782	0.138
	Importance	30	3.10	2.315	0.416

Table 20

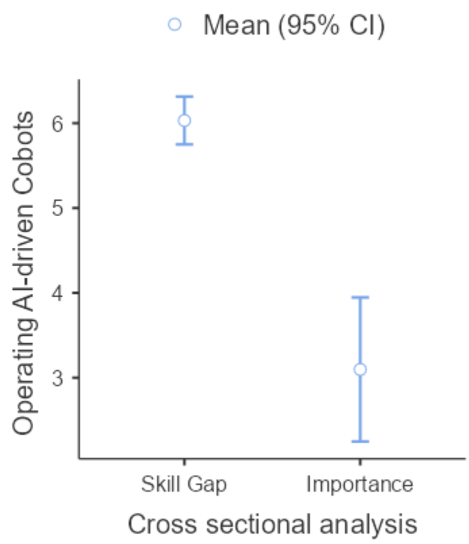

Figure 21

As shown in the Figure 21, The data shows that the skill gap for working collaboratively with AI-driven machinery is high, with a mean of 6.03, while the importance of this skill is notably lower, with a mean of 3.10. In this analysis a higher skill gap mean represents a greater gap in the ability rather than proficiency, this indicates that **workers in underdeveloped countries struggle significantly with operating AI-driven cobots, and managers do not universally consider this skill highly important.**

The graph visually reinforces this distinction, as the data point for the skill gap is much higher than the data point for importance, indicating that workers are broadly seen as lacking this skill, but its necessity is debated among managers. The confidence intervals for importance are much wider than those for the skill gap, which suggests that there is a large variation in how different managers perceive the relevance of cobot operation. In contrast, the mean of the skill gap for operating AI-driven cobots remain more consistent across respondents, showing that the perception of a deficiency in this skill is widespread.

A closer look at the **standard deviations** further illustrates these differences. The **standard deviation for importance (2.315) is significantly higher than for the skill gap (0.782),** meaning that while some managers may view cobot operation as an essential skill, others see it as much less critical. This high variability in importance contrasts with the more stable perception of a skills deficiency, suggesting that while nearly all managers agree that workers struggle with cobot operation, there is no strong consensus on whether this skill is necessary in the factories of different companies.

These findings suggest that while factory workers in underdeveloped countries have a substantial skills deficiency in operating AI-driven cobots, this may not be a universally prioritized skill across industries. The inconsistency in how managers rate its importance indicates that some workplaces may see cobot operation as a necessary capability, while others may not integrate AI-driven collaborative robots into their production processes at all.

III. **Cross-sectional analysis on Adjusting Parameters in AI-driven Machinery Skills:** In Figure 22, the graph compares the responses of S2Q8 ("Our factory workers lack proficiency in adjusting and inputting parameters in AI-driven machinery") and S3Q9 ("Entering and adjusting data inputs for AI-driven machinery, such as parameters, sensor settings, or performance metrics, is an important skill for our factory Worker's), for a higher mean value indicates a greater skill gap rather than proficiency.

Group Descriptives

	Cross sectional analysis	N	Mean	SD	SE
Adjusting Parameters in AI-driven Machinery	**Skill Gap**	30	6.16	1.59	0.281
	Importance	30	4.16	2.08	0.374

Table 21

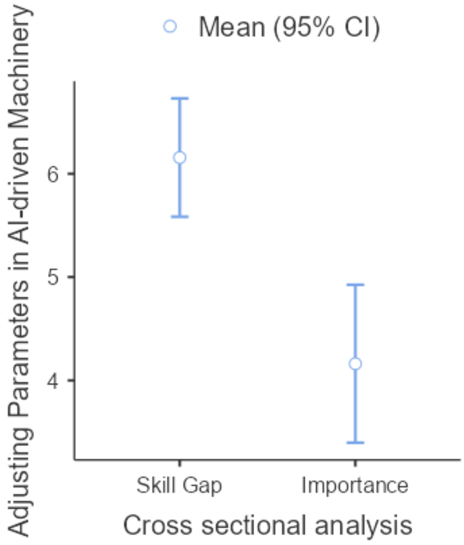

Figure 22

As shown in the Figure 22, The cross-sectional analysis of adjusting parameters in AI-driven machinery in underdeveloped countries reveals a clear gap between the skill levels of workers and the perceived importance of this skill. The data shows that there is **significant skill gap,** with a mean of 6.16 in adjusting parameters in AI-driven machinery, while the **importance of this skill is rated lower,** with a mean of 4.16. Since a higher skill gap mean represents a greater deficiency in ability rather than proficiency, this indicates that workers in underdeveloped countries significantly skills in adjusting and inputting parameters in AI-driven machinery, even though managers do not universally consider this skill highly important.

The graph visually reflects this pattern, as the data point for the skill gap is positioned notably higher than the mean of ‘importance of the skill’, showing that managers widely acknowledge a lack of proficiency in this skill, but opinions on its necessity vary. The confidence intervals for importance are much wider than those for the skill gap, indicating that there is greater variation in how different managers perceive the relevance of adjusting AI parameters. In contrast, the skill gap mean remain more consistent across respondents, meaning that most managers agree on the lack of proficiency in this area.

A closer look at the standard deviations further highlights these differences. The **standard deviation** for importance (2.08) is significantly **higher** than for the skill gap (1.59), suggesting that **some managers see parameter adjustment as an essential skill, while others may not view it as a priority in their specific manufacturing environments.** This contrast in variability suggests that while nearly all managers agree that workers lack the ability to adjust AI parameters, there is no strong consensus on whether this is a critical issue across different factories.

These findings indicate that while factory workers in underdeveloped countries have a considerable deficiency in adjusting AI parameters, this may not be a universally prioritized skill across all industries. The inconsistency in how managers rate its importance suggests that some workplaces may see AI parameter adjustment as a necessary capability, while others may not consider it as highly important. As a result, efforts to close this skills gap may need to be industry-specific, focusing on sectors where precise AI parameter adjustments play a more significant role in daily operations.

Cross sectional analysis of Section 1 and 2

This section examines how manager's perceptions in underdeveloped countries shift when evaluating the same AI-related skills from two different perspectives. Section 1 focuses on assessing the proficiency levels of factory workers, while Section 2 measures the skill gaps for those exact same skills. By comparing these two sections, we can determine whether managers perceive skill gaps as proportional to proficiency levels or if their responses indicate a stronger sense of urgency for certain skills when framed as a gap rather than a proficiency rating. This distinction is important because it reveals whether managers rate skill gaps more severely than implied by proficiency levels, which could influence training priorities and workforce development strategies. Additionally, this comparison helps identify whether some AI-related skills are seen as more operationally critical, leading to greater discrepancies between proficiency and skill gap assessments. Understanding these patterns is particularly valuable in comparing developed and underdeveloped countries, where workforce readiness and AI adoption challenges may differ significantly.

The analysis compares the following **three skills** across **Section 1 and Section 2**, ensuring that the exact same competency is assessed in both sections:

1. **Maintaining AI-driven machinery** (**S1Q5** vs. **S2Q3**)
2. **Using AI-driven quality control systems** (**S1Q10** vs. **S2Q7**)
3. **Collaborating with AI-driven cobots** (**S1Q13** vs. **S2Q9**)

Difference in responses for same question in section 1 and 2:

S. No	Skills	Proficiency level	Skill gap
1	Maintaining AI-driven machinery	1.54	6.75
2	Using AI-driven quality control systems	2.7	5.28
3	Collaborating with AI-driven cobots	3.06	4.19

Table 22

As showing in the table 22, this analysis reveals a **far greater discrepancy** between proficiency and skill gap ratings, reinforcing **urgent workforce challenges** in AI-related skills.

1. **Maintaining AI-driven machinery (S1Q5 vs. S2Q3):** Workers exhibit very low proficiency in maintaining AI-driven machinery, with a mean of 1.54, meaning they severely lack this skill. If proficiency ratings directly translated to skill gaps, the implied gap would be 5.46 (The maximum value in the likert scale minus the mean of the skill, 7 - 1.54). However, the actual skill gap rated by managers in Section 2 is 6.75, showing a **very large difference** between the two ratings. This discrepancy suggests that managers perceive AI maintenance as a much more critical limitation than what proficiency ratings alone indicate. The 1.29-point gap highlights that worker's inability to perform AI maintenance is seen as a major operational risk, with managers emphasizing this limitation even more when explicitly asked to rate the skill gap rather than just assessing proficiency. The far higher skill gap rating in Section 2 suggests that AI maintenance is a top concern in underdeveloped countries, with a significant lack of skilled workers making AI integration and reliability a serious challenge.

2. **Using AI-driven quality control systems (S1Q10 vs. S2Q7):** Workers exhibit low proficiency in using AI-driven quality control systems, with a mean of 2.7, meaning they severely lack this skill. If proficiency ratings directly translated to skill gaps, the implied gap would be 4.3 (The maximum value in the likert scale minus the mean of the skill, 7 - 2.7). However, the mean skill gap rating given by managers in Section 2 is 5.28, which is **higher than expected**. This suggests that when assessing proficiency, managers acknowledge that workers have some familiarity with AI-driven quality control. However, when asked to assess it as a skill gap, they rate the limitation closely higher. The 0.98-point difference between implied and explicit skill gap ratings. This discrepancy indicates that workers demonstrate some familiarity with AI-driven quality control, it is not nearly enough to meet operational expectations, and managers emphasize the need for improvement when the question is framed as a gap rather than proficiency.

3. **Collaborating with AI-driven cobots (S1Q13 vs. S2Q9):** Workers exhibit low proficiency in collaborating with AI-driven cobots, with a mean of 3.06, meaning they lack proficiency but are closer to moderate competency than in other AI-related skills. If proficiency ratings directly translated to skill gaps, the implied gap would be 3.94 (The maximum value in the likert scale minus the mean of the skill, 7 - 3.06), while the explicit skill gap in Section 2 is 4.19, showing a **small difference** in how managers rate the same skill when framed differently. Unlike in the assessment of 'maintaining AI-driven machinery', this discrepancy is not as large, indicating that managers generally assess proficiency and skill gap for cobot collaboration in a similar manner. While the gap is slightly higher when framed as a skill gap, this suggests that managers do not perceive cobot collaboration as a particularly critical workforce limitation, though they acknowledge there is room for improvement.

This analysis indicate that managers assess skill gaps more critically when framed as a gap rather than as a proficiency level.

5.2.2.4 Findings from the Analysis of Underdeveloped Countries

Findings from Sectional analysis

Section 1

The findings from Section 1 highlight varying levels of proficiency among factory workers in AI-driven manufacturing environments. Workers do not demonstrate proficiency in any AI-related skills. Only two areas fall within the moderate proficiency category, and they are 'knowledge of AI safety protocols' and 'participation in AI training programs'. However, these are not technical skills but rather indicators of training participation and safety awareness. The presence of training does not necessarily translate into hands-on proficiency, as workers continue to lack competency across all other AI-related areas. Most core AI operational skills are **severely lacking**, indicating that while workers may have some exposure to these technologies, their ability to apply them in real-world AI-driven environments is highly insufficient. Skills such as adapting to AI technology, operating basic AI-driven machinery, interacting with AI-driven systems, maintaining AI-driven machinery, and troubleshooting AI-related issues all fall into the significantly lacking category. These findings suggest that workers are largely unprepared for AI-integrated manufacturing and require upskilling. Additionally, collaborating with AI-driven cobots falls within the lacking proficiency category, but while some workers may have minimal experience with collaborative robots, their ability to use them efficiently remains inadequate.

Overall, the findings emphasize a severe skill gap in AI readiness among factory workers in underdeveloped countries. The fact that only two areas fall into the moderate proficiency category while the majority of AI-related skills are severely lacking suggests that **workers are not adequately prepared for AI-driven manufacturing**. The data suggests that companies may be focusing more on theoretical knowledge rather than hands-on skill development, as workers demonstrate some understanding of AI safety protocols but lack the ability to operate AI-driven machinery.

Section 2

The findings from Section 2 focus on skill gaps among factory workers, revealing that the most **significant skill gaps** exist in AI maintenance, troubleshooting, issue resolution, and access to continuous learning opportunities. The highest skill gaps are observed in operating and maintaining AI robotic systems, performing AI-related maintenance and troubleshooting, using AI-driven tools to resolve issues, and improving collaboration with AI-driven machinery. Additionally, the most severe skill gap is in accessing continuous learning opportunities in AI technologies, suggesting that workers not only lack AI-related skills but also face significant barriers in acquiring the necessary training to bridge these gaps. A **moderate skill gap** is identified in using AI-driven quality control systems and collaborating with AI-driven cobots, indicating that while workers have some exposure to these technologies, they lack the expertise to use them effectively. These gaps remain substantial enough to hinder operational efficiency, as AI-driven quality control plays a critical role in modern manufacturing processes. One notable finding is the significantly lower skill gap in optimizing AI-driven machinery, suggesting that workers in underdeveloped countries are almost entirely unable to fine-tune, adjust, or optimize AI-driven processes. Additionally, their response to AI technologies is categorized as a significantly low skill gap, indicating that while workers may not reject AI adoption, they lack the necessary training and knowledge to integrate it effectively into their workflow.

Overall, the findings highlight a **severe lack of AI-related skills** among factory workers in underdeveloped countries, particularly in machine operation, troubleshooting, and optimization. The absence of continuous learning opportunities further worsens the situation, preventing workers from gaining the necessary expertise to operate AI-driven systems effectively.

Section 3

The findings from Section 3 reveal that factory managers in underdeveloped countries **highly prioritize** the ability to quickly learn and use new AI-driven machinery. This suggests that the workforce must be adaptable to technological advancements and capable of integrating AI technologies into daily operations. Other highly important skills include proficiency in operating AI-driven machinery, understanding and responding to AI-generated alerts, and proficiency in using AI-based quality control systems. The emphasis on real-time AI alerts and automated quality control suggests that factories require workers who can monitor AI-assisted processes and ensure consistent production quality through automated inspection systems. Several technical skills fall within the **moderate importance** category, including performing routine AI maintenance, controlling advanced AI robotic systems, entering and adjusting data inputs for AI-driven machinery, and managing AI-controlled conveyor systems. These findings indicate that while technical interaction with AI-driven systems is necessary, it is not considered as critical as direct AI operation and rapid adaptability. Understanding and implementing AI safety protocols also falls within this category, suggesting that while safety remains relevant, the primary focus is on efficiency and operational integration of AI-driven systems. A few skills were considered **less important**, including proficiency in using machine learning algorithms, operating AI-driven collaborative robots, and adjusting paths of factory robots. The particularly low emphasis on machine learning algorithms suggests that factory managers do not expect workers to develop or modify AI systems. Instead, their role is focused on operating AI-integrated systems rather than engaging in AI development or customization.

Overall, the findings indicate that workers in underdeveloped countries must focus on quickly adapting to AI technologies, efficiently operating AI-driven machinery, and ensuring smooth production workflows through AI-assisted monitoring and quality control. While some level of technical interaction with AI is necessary, complex AI programming and robotic adjustments are not seen as essential responsibilities for factory workers. These insights highlight the need for structured training programs that emphasize hands-on AI skills to prepare workers for AI-integrated manufacturing environments.

Cross-sectional analysis

cross-sectional analysis comparing skill proficiency Section 1 and Section 3

The cross-sectional analysis comparing skill proficiency (Section 1) and skill importance (Section 3) in underdeveloped countries highlights significant discrepancies between worker's current abilities and managerial deemed importance level in AI-driven manufacturing.

Analysis on skill 'Operating AI-driven Machinery' reveal that workers demonstrate a significantly lacking level of proficiency in '**operating AI-driven machinery**', while managers consider this skill highly important. The graph shows a substantial gap, with importance rated much higher than proficiency, suggesting that current skill levels are far from adequate to meet industry demands. The confidence intervals confirm that the difference is statistically significant, reinforcing that managers overwhelmingly recognize this as a **critical skill**, yet workers are not adequately prepared. Most managers agree on the necessity of this skill, but there is variation in how strongly they perceive its importance, indicating inconsistencies in AI adoption priorities across different workplaces.

A similar pattern is observed from the analysis of skill **'interpreting feedback from AI-driven machinery'**. Workers exhibit a significantly lacking ability in understanding AI-generated feedback, while managers overwhelmingly consider this skill essential. The graph highlights a large gap between proficiency and deemed importance level, indicating that workers struggle with interpreting and responding to AI-generated alerts. The confidence intervals for proficiency and importance do not overlap, reinforcing that this is a widely recognized skills deficiency. Most managers agree on the importance of this skill, while responses regarding worker proficiency vary, suggesting that while **some workers may have a basic understanding, others lack sufficient competency**. This inconsistency in proficiency highlights a need for upskilling to improve AI feedback interpretation and real-time response capabilities.

The analysis of the skill **'operating AI-driven collaborative robots (cobots)'** show a relatively small gap between proficiency and importance. The graph indicates that worker's skill levels and managerial deemed importance level are more aligned compared to other AI-related competencies. Unlike other AI skills, cobot operation is not seen as highly critical by managers, nor do workers exhibit significant competency in this area. The confidence intervals for proficiency and importance overlap considerably, suggesting that this skill is not widely recognized as a priority. However, the higher variability in importance responses indicates that **some managers see cobot operation as essential, while others do not consider it a necessary capability**. This suggests that cobot operation may be relevant in certain manufacturing environments but is not universally required across all factories.

The cross-sectional analysis comparing skill gaps section 2 and section 3

The cross-sectional analysis comparing skill gaps (Section 2) and skill importance (Section 3) further highlights key areas requiring workforce upskilling.

Findings from the analysis of the skill **'operating AI-driven machinery'** indicate a high skill gap, while managers consider this skill highly important. The graph shows that the skill gap score is nearly as high as the importance score, reinforcing that workers significantly lack proficiency in this area. The confidence intervals for skill gap and importance overlap, suggesting that managers widely recognize both the severity of the deficiency and the necessity of the skill. However, there is some **variation in how managers perceive the urgency of addressing this gap**, suggesting differences in AI adoption and workforce training strategies across different workplaces.

Findings from the analysis of the skill **'operating AI-driven collaborative robots (cobots)'** indicate that the skill gap is high, yet the perceived importance of this skill remains notably lower. The graph visually represents this contrast, as the skill gap mean is positioned significantly higher than the importance mean, showing that while workers struggle with cobot operation, managers do not universally deem it essential. The confidence intervals for importance are much wider than those for the skill gap, indicating that some managers view cobot operation as crucial, while others do not see it as a priority. This suggests that the necessity of cobot-related skills varies depending on the industry and specific manufacturing processes.

Findings from adjusting parameters in AI-driven machinery indicate a high skill gap, while managers rate this skill at a moderate level of importance. The graph illustrates a visible discrepancy, with the skill gap positioned notably higher than the importance score. This suggests that while managers acknowledge that workers significantly lack proficiency in adjusting AI parameters, they do not universally consider this skill as essential. The confidence intervals for importance are much wider than those for the skill gap, reinforcing that opinions on the necessity of AI parameter adjustments vary significantly across different manufacturing environments. Some managers see parameter adjustment as a critical skill, while others do not prioritize it, suggesting that the urgency of addressing this gap depends on the specific industry needs.

Overall, these findings highlight major skill gaps in AI-driven machinery operation and AI feedback interpretation, both of which are deemed highly important yet remain areas where workers exhibit a severe lack of proficiency. Meanwhile, skills such as cobot operation and AI parameter adjustments show a more balanced relationship between skill gaps and importance, suggesting they are less of an immediate concern across all industries. While most managers agree on the critical skills needed in AI-driven manufacturing, there is considerable variation in how they perceive worker proficiency and the urgency of closing these gaps, indicating differences in AI adoption and training priorities across different companies.

Cross sectional analysis of section 1 (Proficiency level) and section 2 (Skill gap)

The Cross-sectional analysis between worker proficiency level and perceived skill gaps reveals notable difference in how managers in the underdeveloped countries assess AI-related competencies when the same question is asked differently. In maintaining AI-driven machinery, managers perceive this as a critical workforce limitation, with a significantly higher skill gap rating compared to the implied gap from proficiency scores. This suggests that beyond simply lacking proficiency, the inability to maintain AI-driven machinery is seen as a major operational risk, making it one of the most pressing concerns in underdeveloped countries. The disparity between proficiency and skill gap ratings reflects the urgency managers place on this skill, emphasizing the need for substantial improvement.

For using AI-driven quality control systems, workers demonstrate some familiarity with the skill but still fall far below the required competency level. The skill gap rating given by managers is notably higher than the expected gap from proficiency scores, reinforcing that while workers have some exposure, it is insufficient to meet AI-integrated manufacturing demands. This suggests that when managers assess the skill as a gap rather than a proficiency level, they highlight its importance more critically, indicating that AI-driven quality control remains an area requiring significant upskilling.

In collaborating with AI-driven cobots, the discrepancy between proficiency and skill gap ratings is much smaller compared to the previous two skills. While managers acknowledge that workers lack proficiency in this area, their assessment of the skill gap remains closely aligned with proficiency scores, suggesting that cobot collaboration is not viewed as a major workforce limitation. This implies that, while there is room for improvement, the urgency to address this gap is lower compared to AI maintenance and quality control.

This section indicate that managers perceive AI-related skill gaps more critically when explicitly asked to rate them as gaps rather than as proficiency levels. This shift in perception suggests that the framing of skill assessments influences managerial responses.

What is interesting:

5.2.2.5 Thematic Analysis of qualitative:

Thematic analysis is a widely used qualitative research method that involves identifying, analyzing, and interpreting patterns or themes within qualitative data. It provides a structured approach to understanding the deeper meaning of data, allowing researchers to uncover insights that might otherwise remain hidden. According to Braun and Clarke (2006), thematic analysis is a flexible yet rigorous method that enables researchers to systematically organize and describe qualitative data while offering rich, detailed accounts of the findings. It is particularly valuable when exploring complex social phenomena, as it provides a framework for making sense of varied perspectives. This method typically involves six steps: (1) familiarization with the data, (2) generating initial codes, (3) searching for themes, (4) reviewing themes, (5) defining and naming themes, and (6) producing the final report. These steps make sure a comprehensive analysis, moving from the raw data to well-defined themes that capture the essence of the participants" experiences and viewpoints. Thematic analysis is not tied to a specific theoretical framework, making it adaptable to different research contexts and disciplines (Braun

& Clarke, 2006). In this thesis, thematic analysis is employed to understand the qualitative data gathered from respondents in underdeveloped countries. The analysis focuses on uncovering key themes related to the adoption of AI-driven technologies in manufacturing, including training gaps, resistance to change, and practical challenges. This approach allows for a nuanced understanding of the respondents" perspectives, highlighting the contextual factors that influence the implementation of AI technologies in these regions.

The qualitative data gathered from respondents in underdeveloped countries offers valuable insights into the challenges and realities faced in adopting AI-driven manufacturing technologies. Thematic analysis of this data reveals three prominent themes: **Lack of Structured Training Programs**, **Resistance to Change**, and **Practical Limitations in Skill Development**. These themes are explored in detail below.

I. **Lack of Structured Training Programs:** The data reveals a significant gap in structured training initiatives, with respondents highlighting that while training programs are in progress, they are not yet fully developed. Worker's unfamiliarity with AI technologies is further compounded by educational limitations, making it difficult for them to grasp complex concepts effectively. Moreover, respondents noted that many workers lack motivation and feel insecure about their ability to adapt to new technologies. These findings highlight the necessity of designing training programs that are tailored to the educational background of workers. Training must be gradual and focus on foundational skills to build confidence and promote engagement among workers.

II. **Resistance to Change:** Another critical theme is the resistance to change exhibited by workers. The data suggests that workers prefer stability and are reluctant to modify their established ways of working. This resistance is often driven by a fear of frequent changes and the effort required to learn new methods. Additionally, respondents mentioned that motivating workers to embrace change is a significant challenge. This theme highlights the importance of change management strategies in underdeveloped regions. Providing incentives, fostering a positive learning environment, and emphasizing the benefits of AI adoption could help mitigate resistance and encourage workers to adapt.

III. **Practical Limitations in Skill Development:** The feasibility of training workers on advanced AI-driven skills emerged as a significant concern. Respondents indicated that the skills listed in Section 3 of the survey, such as proficiency in machine learning algorithms or adjusting robot paths, are more appropriate for engineers than factory workers. The data suggests that while these skills are important, training workers on such skills in a practical manufacturing environment is unrealistic. This theme highlights the need to prioritize foundational skills, such as operating AI-driven machinery or responding to system alerts, over more specialized tasks. By focusing on realistic training goals, organizations can improve Worker's performance without overwhelming them with complex demands.

This thematic analysis of qualitative data sheds light on the specific challenges faced by underdeveloped countries in implementing AI-driven manufacturing technologies. The **lack of structured training programs, resistance to change, and practical limitations in skill development** collectively point to the need for a tailored approach.

5.2.3 ANOVA Test

The analysis utilizes **One-Way ANOVA (Welch"s Test)**, a statistical technique used to compare the means of two or more independent groups in this case, respondents from developed and underdeveloped countries. This test evaluates whether the observed differences in the mean mean s of Sections 1, 2, and 3 between the two regions are statistically significant or simply due to random chance.

ANOVA Table:

One-Way ANOVA (Welch's)

	F	df1	df2	p
Current Proficiency (Section 1)	14.38487	1	25.3	<.001
Skill Gap (Section 2)	0.00843	1	13.5	0.928
Perceived Importance (Section 3)	1.24900	1	23.1	0.275

Table 23

From table 23, The results indicate a statistically significant difference in overall proficiency levels (Section 1) between developed and underdeveloped countries. The F-value of 14.38487 suggests a substantial disparity in worker proficiency across AI-driven manufacturing environments, with a p-value of < 0.001, confirming that the difference is highly significant. This means that workers in underdeveloped countries exhibit markedly **lower AI-related proficiency levels** compared to those in developed regions, and this gap is not due to random variation.

However, for Section 2 (Skill Gaps) and Section 3 (Importance of Skills), the results do not indicate statistically significant differences between the two regions. The F-value for Section 2 is 0.00843, with a p-value of 0.928, meaning that managers in both developed and underdeveloped countries perceive AI skill gaps similarly, without a significant difference in their responses. Similarly, for Section 3, the F-value is 1.24876 with a p-value of 0.275, indicating that **managers across both regions assign similar levels of importance** to AI-related skills, without notable variation between developed and underdeveloped economies.

These findings suggest that while actual proficiency levels in AI-related skills differ significantly between developed and underdeveloped countries, the perception of skill gaps and skill importance remains consistent across both regions. This reinforces the idea that despite differing worker competencies, managers globally recognize similar AI skill gaps and prioritize the same AI-related competencies for future workforce development.

Descriptive plots:

Basic Information to read graphs:

- **Mean (Round Circle):** In each graph, the round circle in the middle of the vertical line represents the mean for the respective section. This provides a visual representation of the average perception of respondents in developed and underdeveloped regions.
- **Vertical Line (Confidence Interval):** The vertical line around the mean represents the 95% confidence interval (CI). This interval shows the category within which the true population mean is likely to fall with 95% certainty. A longer line indicates greater variability or uncertainty, as seen in underdeveloped countries in Section 2.
- **Small Horizontal Dashes at the Ends:** These dashes mark the upper and lower bounds of the confidence interval, providing a clear visualization of the category.

I. **Comparison of Section 1 between Developed and Underdeveloped Regions:** Figure 23 provides a Cross-sectional analysis of the mean responses for Section 1, which evaluates the current skill levels of managers in AI-driven manufacturing environments across developed and underdeveloped regions.

Group Descriptives

	Region	N	Mean	SD	SE
Current Proficiency (Section 1)	**Developed**	15	4.17	0.910	0.235
	Underdeveloped	15	2.63	1.273	0.329

Table 24

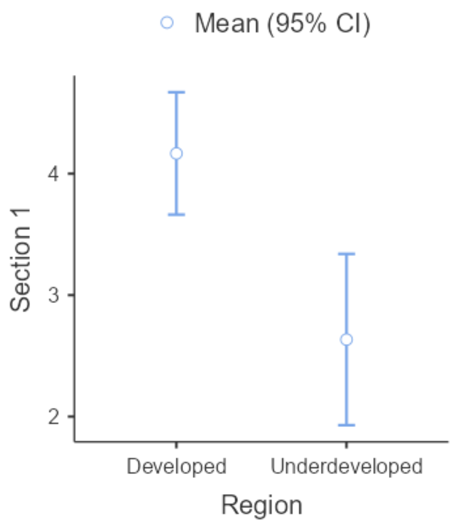

Figure 23

Table 24 provides an overview of the descriptive statistics of the responses related to current proficiency levels (Section 1) in AI-driven manufacturing across developed and underdeveloped countries. In this context, **N** represents the number of questions within Section 1, which contributes to the mean proficiency score for each region. The **mean** represents the average proficiency level reported across all questions in Section 1, indicating the general trend in worker capabilities. The **standard deviation (SD)** measures the variability of responses; a lower SD suggests that responses are closely clustered around the mean, whereas a higher SD indicates greater variation among respondents. The **standard error (SE)** reflects the precision of the mean estimate, with a lower SE implying more confidence in the reported mean values.

The ANOVA analysis for Section 1, comparing developed and underdeveloped countries, highlights a significant difference in proficiency levels between the two regions. The mean proficiency score for developed countries is 4.17, while for underdeveloped countries, it is notably lower at 2.63. This indicates that, on average, workers in developed countries demonstrate a moderate level of proficiency in AI-driven manufacturing, whereas workers in underdeveloped countries exhibit significantly lower capabilities in this domain. The statistical significance of this difference is confirmed by the **F-value (14.4)** and the **p-value (< 0.001)** from the ANOVA test. The high F-value suggests that the difference in proficiency is substantial, and the p-value, being well below the 0.05 threshold, indicates that this difference is statistically significant rather than occurring due to random variation.

The graph visually reinforces these findings, with the proficiency level in developed countries positioned notably higher than that in underdeveloped countries. The confidence intervals for the two regions do not overlap, further supporting the statistical significance of the difference in proficiency. Additionally, the higher standard deviation for underdeveloped countries (1.273) compared to developed countries (0.910) suggests that responses within underdeveloped countries are more varied, with some managers perceiving their workers as having even lower proficiency. The higher standard error (0.329) in underdeveloped countries compared to developed countries (0.235) also indicates less precision in the mean proficiency estimate for underdeveloped regions, reflecting inconsistencies in responses.

Overall, the analysis highlights a significant difference in proficiency between developed and underdeveloped countries in AI-driven manufacturing. While workers in developed countries exhibit a moderate level of competency, those in underdeveloped countries demonstrate considerably lower proficiency, emphasizing the need for targeted upskilling efforts in AI-related manufacturing tasks.

II. **Comparison of Section 2 between Developed and Underdeveloped Regions:** Figure 24 compares the average mean s for Section 2, which focuses on identifying skill gaps among workers in AI-driven manufacturing environments in developed and underdeveloped regions.

Group Descriptives

	Region	N	Mean	SD	SE
Skill Gap (Section 2)	**Developed**	11	5.32	0.776	0.234
	Underdeveloped	11	5.38	1.834	0.550

Table 25

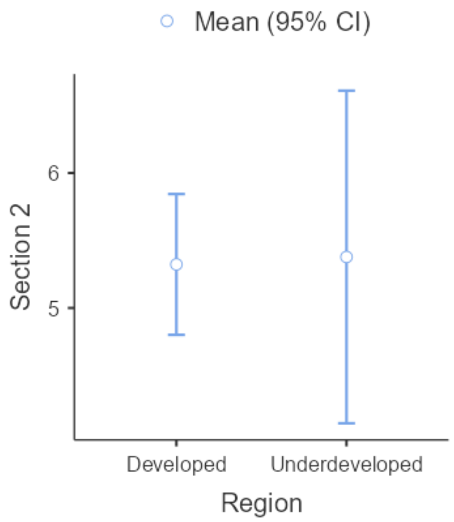

Figure 24

Table 24 provides an overview of the group descriptives of the responses regarding skill gaps in AI-driven manufacturing across developed and underdeveloped countries. In this case, **N** represents the number of questions in Section 2 that assess the perceived skill gaps among factory workers. The **mean** value represents the average skill gap score across these questions, indicating the overall extent to which managers believe workers lack the necessary AI-related skills. A higher mean suggests a more significant skill gap, while a lower mean indicates a smaller gap. **Standard deviation (SD)** measures how much individual responses vary from the mean. A lower SD suggests that respondents largely agree on the severity of the skill gap, while a higher SD indicates greater variability in perceptions. **Standard error (SE)** reflects how much the sample mean might fluctuate if different respondents were surveyed, with a lower SE implying a more precise estimate of the mean.

The findings from the skill gap analysis in Section 2 show that the mean values for both developed and underdeveloped countries are closely aligned, with only a slight difference. This indicates that managers in both regions perceive a similar level of skill deficiency among factory workers when it comes to AI-related tasks. However, the **standard deviation for underdeveloped countries is notably higher than that of developed countries**, suggesting greater variation in how managers assess skill gaps in different workplaces. Some managers may perceive the gap as severe, while others may consider it less pronounced, leading to a broader range of responses. In contrast, developed countries show a more consistent perception of skill gaps, as indicated by a lower standard deviation.

The visual representation in the graph reinforces this pattern. While the means are similar, the confidence intervals for underdeveloped countries are noticeably wider, further emphasizing the inconsistency in manager's assessments of skill gaps. This suggests that while AI skill gaps are a recognized challenge in both regions, the extent of these gaps varies more significantly within underdeveloped countries. The standard error values follow a similar trend, with developed countries showing a more precise estimate compared to the more variable responses in underdeveloped regions.

Overall, these findings indicate that while skill gaps in AI-driven manufacturing are a widespread concern across both developed and underdeveloped countries, the degree to which managers perceive these gaps varies more in underdeveloped regions. This could be due to differences in AI adoption rates, training availability, or industry-specific requirements.

.

III. **Comparison of Section 3 between Developed and Underdeveloped Regions:** Figure 25 illustrates the mean responses for Section 3, which evaluates the importance managers place on various skills for workers in AI-driven manufacturing environments.

Group Descriptives

	Region	N	Mean	SD	SE
Perceived Importance (Section 3)	**Developed**	14	5.41	1.10	0.295
	Underdeveloped	14	4.83	1.60	0.427

Table 26

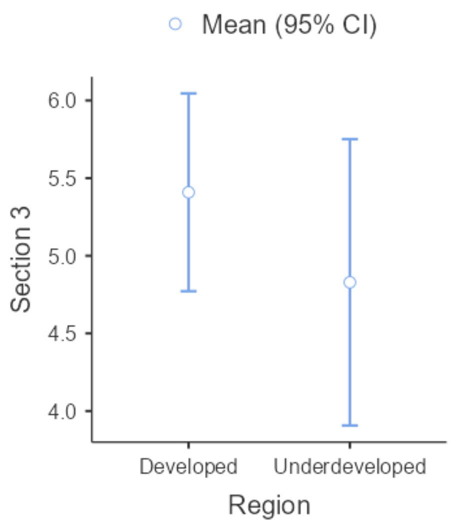

Figure 25

Table 26 presents statistical summaries comparing the perceived importance of AI-driven manufacturing skills (Section 3) between developed and underdeveloped countries. In this context, **N** represents the number of survey questions included in Section 3. The **mean** indicates the average rating given by managers regarding the importance of AI-related skills for factory workers. A higher mean suggests that managers collectively perceive these skills as more critical. The **standard deviation (SD)** reflects how much individual responses deviate from the mean, with a higher SD indicating greater variability in how managers across different regions perceive the importance of these skills. The **standard error (SE)** measures the precision of the mean estimate, with lower SE values indicating that the reported mean is more reliable and consistent across the sample.

The data shows that managers in **developed countries** rate the perceived importance of AI-driven manufacturing skills at **5.41**, whereas managers in **underdeveloped countries** assign a slightly lower rating of **4.83**. This difference suggests that while managers in both regions recognize the significance of these skills, those in developed countries place a slightly higher priority on them. The **standard deviation** for underdeveloped countries (**1.60**) is notably higher than that of developed countries (**1.10**), indicating that opinions on skill importance vary more widely among managers in underdeveloped regions. This suggests that some managers in underdeveloped countries may place high importance on AI-related skills, while others may not see them as an immediate necessity. The **standard error** follows a similar trend, with developed countries having a lower SE (**0.295**) compared to underdeveloped countries (**0.427**), reinforcing that responses from developed regions are more consistent.

The **One-Way ANOVA Analysis** compares the statistical significance of the differences in perceived importance between developed and underdeveloped countries. The **F-value** measures how much variance exists between the two groups relative to the variance within each group. A higher F-value suggests a stronger difference in perceived importance across regions. The **p-value** indicates whether the observed difference is statistically significant. If $p < 0.05$, the difference is considered significant, meaning it is unlikely to have occurred by chance.

The **graph visually represents the findings**, showing that while the importance of AI-related skills is rated higher in developed countries, the confidence intervals for both regions overlap. This indicates that while the perceived importance differs slightly between the two regions, the variation is not substantial enough to suggest a strong statistical distinction. The wider confidence interval for underdeveloped countries reflects the greater variability in responses, reinforcing that opinions on skill importance are less uniform in these regions.

Overall, these findings suggest that managers in both developed and underdeveloped countries acknowledge the necessity of AI-related skills in manufacturing, but those in developed regions exhibit greater consensus in viewing them as a priority. The higher variability in underdeveloped countries indicates that while some companies may be actively investing in AI skills, others may not yet consider them essential for workforce development.

5.3 Comprehensive Insights from the data analysis

Interesting Observations

A particularly interesting finding is that in both developed and underdeveloped countries, managers consistently perceive skill gaps as larger than worker proficiency levels suggest. When asked to rate worker proficiency, managers in both groups provided almost moderate responses, indicating that workers had some level of capability. However, when the same skills were framed in terms of skill gaps, the **responses shifted** significantly, with managers perceiving them as much more severe. This suggests that managers view skill gaps as operational challenges rather than just gaps in knowledge. Another fascinating aspect is that while developed countries have workers with moderate proficiency in AI-related tasks, they still fall short of the deemed importance level required for AI-driven manufacturing. Despite workers being able to operate AI-driven machinery, interact with AI-driven robots, and interpret AI-generated feedback, their abilities are still below expectations, indicating that effective integration of AI requires more than just moderate proficiency. An unexpected yet compelling similarity is that workers in both developed and underdeveloped regions actively participate in AI training programs. While one might assume that workers in underdeveloped countries have limited access to AI-related learning, the data shows that participation in training is common across both regions. However, the effectiveness of these training programs is debatable, as workers in underdeveloped countries still exhibit significant skill gaps despite their engagement in AI training. This raises an important question: **Are training programs in underdeveloped countries ineffective, or is the gap so severe that even ongoing training cannot immediately bridge it?**

Another significant observation is that workers in underdeveloped countries tend to stay with their employers for longer periods compared to those in developed countries. This is particularly important because while developed countries experience higher job mobility, underdeveloped countries have a more stable workforce, this can also be a result of job market and the **excessive/limited employment opportunities** in the regions. However, this stability presents an opportunity for long-term workforce development, as workers who remain in one company for extended periods are better positioned to undergo structured, long-term AI training.

Finally, the gender imbalance in AI-driven manufacturing is nearly identical in both groups, with male respondents being the dominant majority. Despite the widespread adoption of AI technologies, female participation remains low in both developed and underdeveloped regions within the manufacturing sector.

Key Differences Between Developed and Underdeveloped Countries

One of the most fundamental differences is the level of workforce readiness for AI-driven manufacturing. In developed countries, workers exhibit moderate proficiency in many AI-related skills, allowing them to engage with AI-driven systems even if their proficiency is below the deemed importance level. In contrast, workers in underdeveloped countries largely lack proficiency in AI-related tasks, making AI adoption significantly more challenging.

The ability to operate AI-driven machinery is another area where the gap is significant. Workers in developed countries demonstrate moderate proficiency, meaning that they can operate AI-driven systems but require further upskilling. In contrast, workers in underdeveloped countries significantly lack this skill, indicating that AI-driven factories in these regions may struggle with basic AI operations without external support. A major difference also emerges in AI maintenance and troubleshooting. While workers in developed countries struggle with maintaining AI-driven systems, they at least have some exposure to these tasks. However, workers in underdeveloped regions have almost no capability in troubleshooting or maintaining AI-driven machinery, raising a question: **To what extent is AI adopted in manufacturing factories in underdeveloped regions? How is the AI being used?**

Another stark contrast is in the importance assigned to skill adaptability. In developed countries, managers place the highest emphasis on proficiency in AI operations, understanding AI-generated alerts, and optimizing AI-driven systems. In underdeveloped countries, however, the most valued skill is the ability to quickly learn and use new AI-driven machinery. This highlights a fundamental **difference in priorities**: developed countries are refining their existing workforce's AI proficiency, while underdeveloped countries are focused on building a foundation for AI adoption. Additionally, cobot operation is viewed differently across regions. In developed countries, workers are not highly proficient in cobot operation, but managers also do not see this as a top priority. In underdeveloped countries, the skill gap in cobot operation is severe, yet managers still do not consider it highly important. This suggests that AI-driven cobots are not yet widely integrated into underdeveloped regions, making them a low-priority skill for now.

Skill Proficiency and Skill Gaps

1. **Proficiency Levels in AI-Driven Skills**: Workers in developed countries exhibit moderate proficiency in several AI-related skills, including:

    - Operating AI-driven machinery
    - Interacting with AI-driven robots
    - Interpreting AI-generated feedback
    - Collaborating with AI-driven cobots

    While they can perform these tasks, their proficiency remains below the deemed importance level expected for AI-driven manufacturing. Troubleshooting and maintaining AI-driven systems, adjusting AI-driven parameters, and optimizing AI machinery remain significant challenges even for workers in developed countries.

    In underdeveloped countries, proficiency in AI-related tasks is almost entirely absent. The only skills where workers show some capabilities are:

    - Following AI safety protocols
    - Participating in AI training programs

However, these are not technical skills but rather indications of a willingness to learn and follow AI-related procedures. All other AI-related skills fall into the significantly lacking proficiency category.

2. Skill Gaps in AI-Driven Manufacturing

The largest skill gaps in developed countries exist in:

- AI troubleshooting
- Maintaining AI-driven machinery
- Optimizing AI-driven systems

While workers in developed countries exhibit moderate proficiency in operating AI systems, they struggle with AI maintenance and troubleshooting, making these high-priority areas for upskilling.

In underdeveloped countries, the skill gaps are far more severe. The highest skill gaps exist in:

- Operating AI-driven machinery
- Troubleshooting AI-driven systems
- Using AI-driven quality control systems
- Collaborating with AI-driven robots
- Accessing AI-related learning opportunities

The most critical skill gap in underdeveloped countries is the lack of access to AI-related continuous learning opportunities. Workers in underdeveloped regions not only lack proficiency in AI skills but also lack the resources and training necessary to bridge these gaps.

Skill Importance and Future Workforce Development

Highly Important Skills in Developed Countries
In developed countries, the three most highly important skills for AI-driven manufacturing are:

1. Operating AI-driven machinery
2. Understanding and responding to AI-generated alerts
3. Optimizing AI-driven systems

This indicates that developed countries are prioritizing technical proficiency in AI operations, ensuring that workers can engage with automated systems efficiently.

Highly Important Skills in Underdeveloped Countries
In underdeveloped countries, the most highly important skill is the ability to quickly learn and use new AI-driven machinery, however this is not a technical skill. Other important skills include:

1. Operating AI-driven machinery
2. Understanding AI-generated feedback
3. Using AI-based quality control systems

This indicates that underdeveloped countries are not yet focused on fine-tuning AI proficiency but rather on preparing workers to integrate AI technologies into manufacturing environments.

The data highlights that workforce readiness for AI-driven manufacturing varies significantly between developed and underdeveloped countries revealing key insights into the challenges and opportunities in shaping the future of AI integration in the manufacturing sector.

5.4 Competency Model

Competency Model for factory workers in AI-driven manufacturing

This competency model has been developed to address the evolving skill requirements of factory workers in AI-driven manufacturing environments. Based on the structured framework proposed by **Marrelli et al. (2005)** and supported by survey findings from **Chapter 5**, this model highlights the key competencies necessary for workers to adapt to and excel within AI-integrated production systems. The model addresses skill gaps identified across both **developed and underdeveloped countries** and ensures that training strategies are aligned with current industry needs.

The model is organized into five core components:

1. **Core Competencies** – Fundamental AI skills required for all workers.
2. **Advanced Competencies** – Specialized skills for higher proficiency roles.
3. **AI Continuous Learning Competencies** – Skills ensuring ongoing workforce adaptability.
4. **AI Workforce Adaptability Competencies** – Competencies supporting readiness for AI-driven transformations.
5. **Regional Adaptation** – Competency differences tailored to the specific needs of developed and underdeveloped countries.

1. Core Competencies

Core competencies focus on fundamental AI skills necessary for all workers in AI-driven manufacturing environments. These competencies ensure that employees can effectively interact with AI systems and participate in AI-supported workflows.

Competency	Basic Level	Intermediate Level	Advanced Level
Operating AI-driven machinery	Reads AI system dashboards	Operates AI-driven machines with minimal supervision	Optimizes AI-driven workflows for efficiency

Competency	Basic Level	Intermediate Level	Advanced Level
Interpreting AI-generated feedback	Recognizes AI alerts but requires guidance	Uses AI-generated data to adjust production	Implements AI-driven decision-making strategies
Collaborating with AI-driven cobots	Works under supervision with cobots	Adjusts cobot operations based on task requirements	Leads integration of cobots into production processes
AI Safety Protocols & Compliance	Aware of AI-related safety procedures	Implements AI-driven safety automation	Ensures AI compliance in production processes

Table 27

2. Advanced Competencies

Advanced competencies target specialized skills necessary for higher-level roles within AI-driven manufacturing environments. These competencies enable workers to troubleshoot systems, maintain AI equipment, and oversee AI-integrated quality control processes.

Competency	Basic Level	Intermediate Level	Advanced Level
AI System Troubleshooting	Identifies minor operational faults	Diagnoses system errors and applies corrective measures	Leads AI system troubleshooting and optimization
Predictive Maintenance Using AI	Understands AI-generated maintenance alerts	Uses AI-based predictive tools to schedule maintenance	Implements and improves AI-driven maintenance strategies
AI-Based Quality Control	Assists in AI-monitored quality control	Operates AI-driven inspection systems	Leads AI-integrated quality assurance and defect detection
Managing AI-Controlled Conveyor Systems	Observes AI-managed logistics systems	Operates AI-driven material handling systems	Oversees AI logistics and factory automation

Table 28

3. AI Continuous Learning Competencies

These competencies emphasize lifelong learning and continuous skill development in AI-driven manufacturing. Workers must stay current with AI advancements, engage with new technologies, and actively seek opportunities for growth.

Competency	Basic Level	Intermediate Level	Advanced Level
AI Learning Engagement	Participates in introductory AI training programs	Pursues regular AI skill development through formal courses	Engages in advanced AI research, certification, and mentoring

Competency	Basic Level	Intermediate Level	Advanced Level
Staying Updated with AI Advancements	Reads basic AI industry updates	Applies knowledge from AI advancements in day-to-day tasks	Leads organizational adaptation to emerging AI technologies
Knowledge Sharing and Collaboration	Shares basic AI knowledge with peers	Participates in team-based AI learning initiatives	Leads collaborative AI innovation efforts within the organization

Table 29

4. AI Workforce Adaptability Competencies

These competencies focus on a worker's ability to adjust to AI-driven changes in the manufacturing environment, ensuring smooth transitions and operational efficiency.

Competency	Basic Level	Intermediate Level	Advanced Level
Ability to Adapt to AI-Driven Changes	Demonstrates openness to AI-related changes	Adjusts workflows in response to AI-driven changes	Leads strategic adaptation of AI-driven changes across operations
Flexibility in AI-Driven Production Processes	Works in AI-assisted workflows with supervision	Transitions smoothly between manual tasks and AI-assisted operations	Designs and implements AI-human collaborative workflows
Problem-Solving in AI-Integrated Workflows	Identifies AI-related issues and seeks assistance	Applies AI problem-solving techniques independently	Develops innovative AI-based solutions for process optimization
Collaboration with AI & Human Teams	Works effectively within AI-human teams	Coordinates AI-assisted collaborations within production units	Develops strategies to enhance AI-human synergy

Table 29

5. Regional Adaptation

This model recognizes regional differences in AI readiness and technological adoption, distinguishing between the needs of developed and underdeveloped countries.

In **developed countries**, the focus should be on enhancing advanced competencies such as AI troubleshooting, predictive maintenance, and AI-based decision-making. Training programs should emphasize continuous learning, fostering innovation and promoting leadership roles in AI system management. Workers should also be equipped to lead AI-human integration efforts and drive organizational transformation through AI technologies.

In **underdeveloped countries**, the priority is to build foundational AI knowledge through structured training programs. Emphasis should be placed on developing core competencies, fostering AI literacy, and introducing continuous learning initiatives that allow workers to gradually engage with AI systems.

Adaptability training should focus on helping workers become comfortable with technological shifts, ensuring a smooth transition from manual to AI-assisted tasks.

6. Implementation & Workforce Training Strategy

This competency model serves as a comprehensive framework for guiding training and assessment to align AI workforce readiness with industry expectations. In developed countries, the focus should be on enhancing advanced competencies while fostering continuous learning and adaptability. Workers are expected to develop skills that allow them to manage AI-driven systems efficiently and take a leading role in integrating AI technologies into production processes. In underdeveloped countries, the priority is to build foundational AI knowledge and practical skills through structured training initiatives. This approach involves fostering AI literacy, improving basic AI operations, and providing supervised training in troubleshooting and quality assurance. Training should also focus on gradually increasing workers' comfort with AI systems, enabling them to transition from basic operations to more complex AI-driven tasks over time. Competency-based recruitment strategies should be employed across both regions to ensure that new hires possess the necessary skills and adaptability for AI-integrated roles. Skills assessments should be implemented systematically to evaluate the current workforce's readiness for AI-driven manufacturing environments. Regular evaluations help workers progress through the competency levels, advancing from basic to specialized roles.

This competency model provides a structured and practical framework for addressing AI-related workforce training needs. By integrating continuous learning, technical skill development, and adaptability competencies, the model supports long-term workforce readiness and promotes operational efficiency in AI-driven manufacturing environments. It ensures that workers across both developed and underdeveloped countries are equipped to meet the demands of technological transformation, fostering a skilled and adaptable workforce capable of thriving in AI-integrated production systems.

6. Discussion

6.1 Literature review vs. Survey findings

The integration of Artificial Intelligence (AI) into automobile manufacturing has been extensively discussed in the literature review, emphasizing its transformative role in reshaping workforce skills, optimizing production processes, and enhancing efficiency through automation. Theoretical insights from the literature review stress the importance of advanced technical skills, such as programming, machine learning, and human-robot collaboration, as prerequisites for workers adapting to AI-driven environments (Mueller & Mezhuyev, 2022; Vermesan et al., 2021). However, empirical findings from this study highlight discrepancies between these theoretical deemed importance level and the practical realities of workforce readiness, skill prioritization, and AI adoption across different regions. Survey data reveal that workers and managers prioritize foundational skills over specialized technical skills, emphasizing the necessity of context-driven strategies for AI workforce integration.

Advanced Technical Skills vs. Foundational Skills

The literature strongly advocates for the development of advanced technical skills, including proficiency in programming AI systems, managing machine learning algorithms, and configuring robotic systems for production efficiency (Benotsmane et al., 2021; Hofmann et al., 2017). Studies suggest that technical proficiency in these areas improves predictive maintenance, enhances product quality, and streamlines factory operations. Companies like General Motors utilize machine learning for optimizing product prototyping, highlighting programming as a fundamental requirement for AI-driven manufacturing (Vermesan et al., 2021)

In contrast, the survey data challenges this notion, as respondents consistently ranked foundational skills higher than advanced technical skills. As shown in **Figure 6**, proficiency in operating AI-driven machinery and responding to system alerts were rated among the most critical skills, while programming ranked among the least important. This misalignment suggests that theoretical emphasis on programming and AI-specific expertise may not reflect the immediate realities of workforce requirements. Additionally, thematic analysis revealed that in underdeveloped regions, many workers lack structured training and basic education in AI technologies, making it impractical to focus on skills without first establishing a strong technical foundation.

Human-Robot Collaboration: Aspiration vs. Implementation

Human-robot collaboration (HRC) is frequently cited in the literature as a defining feature of AI-driven manufacturing, with collaborative robots (cobots) enhancing flexibility and improving production efficiency (Lijffijt et al., n.d.; Matheson et al., 2019). Case studies from BMW and Audi showcase the seamless integration of cobots in assembly processes, reducing errors and enabling greater human-machine synergy (Jain & Kulkarni, 2022; Vermesan et al., 2021). However, practical findings from the survey indicate moderate gaps in cobot-related skills (**Figure 9**), with qualitative data highlighting significant resistance to change among workers.

Thematic analysis identified **Resistance to Change** as a key barrier to AI adoption. Respondents from underdeveloped regions noted that workers "prefer stability over frequent workflow changes" and often struggle with motivation when adapting to new systems. This aligns with (Espina-Romero et al., 2024) findings that cultural and psychological resistance can impede technological adoption, particularly in environments where AI implementation is still in its early stages. The contrast between theoretical deemed importance level of seamless human-robot collaboration and the practical reality of worker resistance undermean s the need for phased implementation strategies that incorporate change management and worker engagement.

Regional Disparities: Theoretical Acknowledgment vs. Empirical Severity

Theoretical studies acknowledge that AI adoption varies significantly between developed and underdeveloped regions, with factors such as infrastructure, access to training, and investment levels influencing workforce readiness (Amejwal et al., 2022; Mueller & Mezhuyev, 2022). While research highlights this disparity, empirical data from the survey quantifies its severity.

As shown in **Figure 23**, developed regions reported higher proficiency in foundational AI-related skills (mean: 4.17) compared to underdeveloped regions (mean: 2.63). While 95% of respondents in developed regions had experience working in AI-driven environments, a superficially similar 94% in underdeveloped regions masked significant qualitative differences. Thematic analysis revealed that in underdeveloped regions, training programs are "in progress but not yet fully structured," and many workers lack confidence in their ability to adapt to AI technologies. These findings corroborate (Cohen

& Gal, 2024) research on workforce readiness disparities, emphasizing that AI training initiatives must be tailored to regional contexts rather than assuming uniform adoption skills.

Predictive Maintenance: Theoretical Promise vs. Practical Limitations

Predictive maintenance is lauded in theoretical literature as a transformative application of AI, reducing downtime through IoT-enabled analytics and real-time data monitoring (Arents et al., 2021; Keleko et al., 2022). However, survey respondents in underdeveloped regions ranked predictive maintenance skills lower (**Figure 28**), with qualitative feedback indicating that many workers lack the technical literacy required to interpret sensor data and make informed maintenance decisions.

Thematic analysis further reinforced **Practical Limitations in Skill Development**, with respondents noting that if workers were expected to master all AI-related skills listed in **Section 3**, "they would be engineers." This reflects the findings of (Madhavaram et al., 2024), who argue that AI implementation often outpaces workforce upskilling efforts, leaving workers unprepared for advanced roles. These findings suggest that while predictive maintenance is conceptually valuable, its practical application requires significant workforce training and adaptation.

6.2 Commonalities Between Theory and Practice

Despite these contrasts, several areas show alignment between theoretical insights and empirical findings:

Continuous Learning-
Both the literature (Arena et al., 2021) and survey respondents emphasize the necessity of **continuous learning** to keep pace with AI advancements. Thematic analysis highlighted a strong recognition among respondents that training programs are necessary, even though they remain unstructured in underdeveloped regions.

Safety Protocols-
Safety in AI-driven manufacturing is a critical focus in academic research (Matheson et al., 2019), and survey findings validate its importance. **Figure 6** reveals that safety-related skills, such as responding to AI-generated alerts, were highly rated across all regions, reinforcing the need for safety training as AI adoption increases.

Ethical Considerations-
Theoretical discussions on AI emphasize concerns regarding algorithmic bias, job displacement, and data privacy (Dolgui et al., 2024). These concerns were also echoed in qualitative survey responses, where managers noted worker anxieties regarding frequent AI-driven changes and job security. These findings highlight the need for ethical oversight in AI deployment strategies.

This discussion bridges the gap between theoretical deemed importance level and practical realities, demonstrating that while AI's transformative potential is well-established, its successful implementation requires a workforce strategy aligned with immediate and long-term needs. Theoretical literature advocates for advanced technical skills, but survey findings highlight that workers and managers prioritize foundational skills, emphasizing operational readiness over programming expertise. Additionally, worker resistance to change, training gaps, and regional disparities present significant challenges to AI adoption, necessitating tailored workforce development initiatives. By focusing on foundational skill-building, managing cultural resistance, and addressing regional inequities, industry leaders, educators, and policymakers can make sure a more inclusive and sustainable AI transition in automobile manufacturing.

7. Recommendations/Communication

The results will be communicated to relevant stakeholders, including industry leaders, policymakers, and educators, to inform workforce development strategies. Based on the findings from the literature review and survey analysis, the following recommendations are proposed for stakeholders. These recommendations provide guidance on actions stakeholders can take to improve workforce readiness and support the integration of Artificial Intelligence (AI) into automobile manufacturing environments.

I. Industry Leaders and Manufacturers-
Industry leaders must address the challenges of integrating Artificial Intelligence (AI) into manufacturing environments by implementing targeted measures. A key priority is the development of structured training programs tailored to both foundational and AI skills. The study titled "Artificial Intelligence Application and High-Performance Work Systems in the Manufacturing Sector" highlights that training initiatives aligned with High-Performance Work Systems (HPWS) greatly improve workforce readiness (Zahoor et al., 2024). Such programs should utilize AI-powered simulations and real-world learning scenarios to develop skills in troubleshooting and system management. For example, structured training methods aligned with employee potential development frameworks could lead to improved worker engagement and technical competency (Zahoor et al., 2024). These initiatives must be scalable to make sure accessibility for workers in underdeveloped regions. The resistance to change among workers is another significant barrier, especially in underdeveloped regions. The study titled "Assessing the Factors Influencing the Adoption of Generative Artificial Intelligence in the Manufacturing Sector" highlights strategies that address psychological barriers, such as offering incentives and engaging employees in participatory decision-making during AI implementation. Clear communication regarding the advantages of AI, such as improved efficiency and safety, is essential. Setting short-term objectives that yield observable results can serve to encourage employees in the adoption of new technologies. Additionally, integrating feedback mechanisms within implementation plans can make sure that concerns of workers are addressed effectively (Rath et al., 2023).

To reduce regional disparities, industry leaders must work with educational institutions and policymakers to establish scalable and affordable training approaches. A study titled "The Role of Structured Training in Addressing Regional Skill Gaps for AI Adoption" highlights the importance of public-private partnerships in bridging these gaps. The development of AI skill-building programs that are specifically designed to address the distinct needs of underdeveloped regions has the potential to foster equitable opportunities for the workforce. For instance, utilizing digital platforms and AI-enabled learning tools for self-paced education can provide necessary flexibility and accessibility to factory workers (Patil, n.d.). It is essential for these programs to focus on standardizing skill development in order to align with international workforce standards. Ethical concerns surrounding AI, such as data privacy, algorithmic bias, and surveillance, require reliable management frameworks. The research titled "Artificial Intelligence Application and High-Performance Work Systems in the Manufacturing Sector" suggests the establishment of AI Ethics Committees within organizations to promote transparency and accountability. These committees can monitor AI deployment and make sure compliance with international standards such as GDPR. The integration of ethics training within workforce development programs is of major significance. For example, training modules focused on responsible AI use and privacy practices can build trust among workers while promoting responsible technology adoption (Zahoor et al., 2024). Establishing clear protocols for data handling and integrating transparency mechanisms in AI systems is essential for ensuring ethical compliance.

It is essential for industry leaders to strike a balance between investing in AI tools and emphasizing the development of foundational skills, especially in underdeveloped regions where training opportunities are often inconsistent.

II. Educational Institutions and Training Providers-

Educational institutions and training providers must prioritize updating frameworks to meet the demands of AI-driven manufacturing environments. A significant area for improvements is the Unified Theory of Acceptance and Use of Technology (UTAUT) model. The study titled "Revisiting Unified Theory of Technology and Use of Technology Using Meta-analytic Structural Equation Modelling" highlights that while the UTAUT model provides a robust foundation for understanding user acceptance of technology, it lacks adaptability for the dynamic nature of AI technology. As AI continues to evolve, institutions must focus on improving the UTAUT framework to incorporate dimensions like real-time system evolution, adaptive intelligence, and user-specific personalization, which are crucial to modern AI adoption (Or, 2023). Curriculum updates should include AI-driven learning tools that reflect the changing technological landscape. The study titled "The Impact of Artificial Intelligence on Higher Education" This empirical study suggests the integration of AI-powered simulations, interactive learning platforms, and hands-on experimentation as effective methods for training future workforce in the management of cobots, predictive maintenance, and AI-assisted decision-making. These methods offer immersive experiences that enhance students" readiness for workplaces integrated with AI technologies. Institutions should incorporate AI-based adaptive learning systems, which adjust the curriculum dynamically based on student performance, ensuring more personalized and effective learning experiences (Slimi, 2023).

Additionally, Collaboration with industries is crucial for keeping educational materials aligned with industry needs. The study titled "Developing an AI Framework for Aligning Academic Programs to the Digital Enterprise" emphasizes the role of AI in curriculum design, urging that institutions partner with AI-driven industries to tailor programs that meet the workforce demands of AI-powered manufacturing. Public-private partnerships can facilitate knowledge transfer, enabling students to work with real-world AI applications before entering the workforce (Nyale et al., 2024). To address ethical concerns in AI education, institutions must develop comprehensive training on AI ethics, bias mitigation, and data privacy. The study titled "Artificial Intelligence Ethics from the Perspective of Educational Technology Companies and Schools" emphasizes the importance of instilling ethical responsibility in AI usage, ensuring that future professionals understand issues such as algorithmic bias, fairness in automated decision-making, and AI transparency, integrating ethics modules into AI-related courses can help students navigate complex ethical dilemmas in AI-driven workplaces (Nyale et al., 2024). Educators must revise curricula to prioritize practical skills in AI operations while introducing advanced topics incrementally to prevent overwhelming workers, by revising the UTAUT model, integrating AI-driven learning systems, fostering industry collaborations, and strengthening AI ethics training, educational institutions and training providers can better prepare students for the evolving demands of AI-powered manufacturing environments. These initiatives will make sure that graduates possess not only technical expertise but also the adaptability and ethical awareness required to thrive in an AI-integrated workforce.

III. Policymakers and Governments-

Policymakers and governments are crucial stakeholders in addressing the challenges associated with integrating Artificial Intelligence (AI) in manufacturing environments.

The study "Analyzing the Direct Role of Governmental Organizations in Artificial Intelligence Innovation" emphasizes the importance of governments investing in AI training programs and research initiatives to enhance workforce readiness. Policymakers should establish public AI training centers designed to equip workers with the skills necessary for AI-integrated roles (Park, 2024). Public-private partnerships, as highlighted in "Evaluating Public-Private Partnerships for Technological Growth in AI" can play a pivotal role in creating accessible and industry-aligned training programs. Additionally, providing tax incentives for industries investing in AI reskilling programs can further support sustainable AI adoption (Plikas et al., 2024). Furthermore, Regulatory oversight is critical for ethical AI governance. The study "Addressing Ethical Challenges in AI Governance" recommends forming national AI ethics boards tasked with overseeing compliance with standards such as GDPR. These boards can monitor transparency, fairness, and worker protection in AI-driven systems, ensuring responsible AI adoption. Governments should also enforce AI transparency mandates, requiring organizations to disclose decision-making processes and address algorithmic biases (Wilczek et al., 2024). Additionally, Participation in global AI policy discussions is essential to align national regulations with international frameworks. The study "Global AI Policy and Standardization Trends" highlights the importance of cross-border collaborations in harmonizing AI regulations and sharing best practices. Governments must actively engage in international AI policy bodies to make sure that their national strategies remain globally relevant and ethical (De Almeida et al., 2021). Policymakers must address infrastructure gaps and encourage public-private partnerships to enhance AI training accessibility, ensuring workforce preparedness in diverse regional contexts (Plikas et al., 2024).

By implementing these measures, including investments in AI training, fostering public-private collaborations, enforcing ethical AI regulations, and participating in global policymaking, governments can effectively address the gaps identified and create a robust framework for AI-driven manufacturing.

IV. Managers in Developed and Underdeveloped Regions-

Managers operating in both developed and underdeveloped regions face unique challenges in navigating the integration of Artificial Intelligence (AI) into manufacturing processes. These challenges include addressing workforce skill gaps, adapting to organizational cultures resistant to change, and implementing effective strategies for AI adoption.

A significant focus for managers should be addressing skill disparities within their workforce. The study "Enablers of Artificial Intelligence Adoption and Implementation in Production Systems" emphasizes the importance of training programs tailored to both organizational needs and employee capacities. Key enablers such as top management support, IT infrastructure readiness, and organizational culture significantly impact the success of AI integration (Merhi & Harfouche, 2024). Managers must champion robustly train initiatives that provide employees with hands-on experience using AI tools, focusing on practical applications like predictive maintenance, data analytics, and human-robot collaboration. This makes sure that employees are adequately prepared to operate in AI-enhanced environments and helps build organizational resilience against technological disruptions.

Resistance to change remains a pervasive issue in organizations adopting AI. The study "Adoption Challenges of AI Systems in Operational Management" highlights how resistance often stems from inadequate communication about the benefits of new technologies and fear of job displacement (Dr. Aajaz Ahmad Hajam & Alphonsa S John, 2024). Managers should implement participatory decision-making practices that involve employees in the planning and deployment of AI systems. Transparent communication regarding the advantages of AI such as efficiency gains and enhanced safety can alleviate worker apprehension. Furthermore, offering incentives like skill-based promotions and recognition programs can motivate employees to embrace AI-driven operational changes (Dr. Aajaz Ahmad Hajam & Alphonsa S John, 2024). Regional disparities in AI adoption present another critical challenge. The study "Adapting AI for Equitable Workforce Development in Manufacturing" identifies the lack of resources and infrastructure as significant barriers in underdeveloped regions (Madonsela, 2023). Managers in these regions should collaborate with industry associations and policymakers to secure funding for infrastructure development and access to cutting-edge AI technologies. Public-private partnerships can provide essential support for creating localized training modules that align with global AI standards while addressing regional nuances. Finally, ethical considerations are paramount for maintaining trust and transparency in AI-driven operations. The study "Ethics in AI Implementation: Balancing Innovation and Responsibility" recommends integrating ethics training into workforce development programs to address issues like algorithmic bias and data privacy (Dolgui et al., 2024). Managers should establish clear guidelines for ethical AI use and conduct regular audits to make sure compliance with international standards. By embedding ethical principles into their organizational strategies, managers can foster a culture of responsibility and trust, which is essential for the sustainable adoption of AI technologies.

Through a combination of targeted training, transparent communication, collaborative partnerships, and ethical oversight, managers can successfully navigate the complexities of AI adoption. These measures will not only enhance workforce readiness but also make sure the long-term sustainability of AI-driven manufacturing systems across diverse regional contexts.

V. For Global Industry Associations-

Global industry associations have a critical role in promoting the adoption and advancement of AI technologies within the manufacturing sector. They act as bridges between regional industry leaders, policymakers, and educational institutions to make sure a standardized, ethical, and collaborative approach to AI integration. Key challenges such as lack of interoperability, disparities in AI adoption rates across borders, and the absence of unified ethical frameworks can be addressed through collective action led by these associations. The study "International Collaboration in AI Research and Development" emphasizes the importance of cross-border partnerships for pooling resources, sharing expertise, and addressing diverse challenges, including climate change and cybersecurity (Kseng, 2024). Global industry associations should foster platforms for collaborative AI research, creating international networks to promote the exchange of knowledge and innovations. For instance, establishing joint research hubs in underrepresented regions can address regional disparities and expand access to AI technologies (Kseng, 2024) To enhance ethical AI practices, global associations can draw insights from the "Achieving Cross-Border Government Innovation" report, which highlights the need for globally harmonized standards and governance mechanisms (Oecd, 2021). Associations should lead initiatives to develop universal ethical guidelines, ensuring transparency and accountability in AI applications. They could advocate for the formation of global ethics committees to oversee AI deployments and address biases in technology implementation (Oecd, 2021).

The study “Cross-Border Technology Integration in the Field of Artificial Intelligence” highlights the role of standardization in optimizing AI integration across industries (Qiu et al., 2023). Associations can spearhead the development of interoperable frameworks and protocols, ensuring seamless AI integration across borders. This includes establishing benchmarks for data sharing and fostering the adoption of universal AI standards to streamline global collaboration.

Moreover, industry associations should focus on capacity building through global talent development programs. The study “AI-enabled Knowledge Sharing and Learning: Redesigning Roles and Processes” suggests leveraging AI to redesign training processes, enhancing workforce readiness for AI technologies (Sundaresan & Zhang, 2022). Associations can collaborate with regional stakeholders to create AI-driven learning platforms, offering accessible, scalable, and tailored training solutions. Finally, associations should address the challenges of unequal resource distribution highlighted in “Achieving Cross-Border Government Innovation”. Initiatives such as shared funding mechanisms for AI projects and the promotion of open innovation platforms can help redistribute resources more equitably, fostering global AI adoption and innovation (Oecd, 2021).

By focusing on fostering collaboration, ethical governance, standardization, and resource equity, global industry associations can accelerate the transformative potential of AI technologies in the manufacturing sector while ensuring their responsible and inclusive integration.

8. Conclusion

The rapid integration of Artificial Intelligence (AI) into automobile manufacturing has ushered in a transformative era, reshaping production processes, workforce dynamics, and global competitiveness. This thesis sought to answer the central research question: “What skills are most important for factory workers to learn and adapt to in AI-driven automobile manufacturing?” By examining workforce readiness across developed and underdeveloped regions, the study reveals critical insights into the interplay between technological advancements, skill requirements, and socio-economic challenges. The findings undermean a complex landscape where theoretical aspirations often diverge from practical realities, necessitating a nuanced approach to workforce development.

The analysis demonstrated that foundational technical skills, such as operating AI-driven machinery, interpreting system alerts, and adhering to safety protocols, are prioritized over skills like programming or machine learning expertise. While literature emphasizes the necessity of specialized technical skills for managing AI systems (Hofmann et al., 2017) (Hofmann et al., 2017; Benoismane et al., 2020), survey data from both regions highlighted that workers and managers gravitate toward operational proficiency as the immediate priority. This misalignment suggests that theoretical frameworks may overestimate the readiness of workforces, particularly in underdeveloped regions, to engage with highly technical AI applications. Instead, incremental skill development beginning with foundational skills is essential to build confidence and adaptability, especially in contexts where structured training programs are still nascent (Cohen & Gal, 2024; Madhavaram et al., 2024). Regional disparities emerged as a defining challenge, with ANOVA results confirming significant differences in skill levels between developed and underdeveloped regions (F-value: 14.38, $p < 0.001$). While 95% of respondents in developed countries reported direct experience with AI-driven systems, qualitative feedback from underdeveloped regions revealed systemic barriers, including limited access to advanced technologies, outdated educational curricula, and inconsistent training infrastructure (Espina-Romero et al., 2024; Mueller & Mezhuyev, 2022). For instance, thematic analysis highlighted that workers in regions like Nigeria and Pakistan often rely on manual labour and traditional practices, creating a cyclical dependency that hinders AI adoption. These disparities are exacerbated by cultural resistance to technological change, where fear of job displacement and mistrust of automation deter workers from embracing new systems (Sinha & Lee, 2024). Addressing these challenges requires more than technical upskilling; it demands holistic strategies that integrate psychological support, transparent communication, and incentives to foster a culture of adaptability.

Safety and ethical considerations emerged as universal priorities across all regions. Worker's ability to interpret AI-generated alerts and comply with safety protocols was consistently rated as critical, aligning with literature on human-robot collaboration and workplace (Arena et al., 2021; Matheson et al., 2019). However, ethical concerns such as algorithmic bias, data privacy, and equitable access to training remained unaddressed in practice. Thematic analysis revealed that managers in underdeveloped regions often lack the resources to implement robust ethical frameworks, leading to ad-hoc compliance with international standards. This gap undermean s the need for global industry associations and policymakers to establish harmonized ethical guidelines and accountability mechanisms, ensuring that AI adoption prioritizes worker well-being alongside productivity gains (Dolgui et al., 2024).

The study's findings validate hypotheses **H1** and **H3**, confirming that advanced technical skills are indispensable but must be contextualized within foundational skills. Hypothesis **H2** was partially supported, as skill alignment necessitates region-specific adaptations rather than universal training models. The research also contributes to the "Unified Theory of Acceptance and Use of Technology (UTAUT)" by highlighting the dynamic nature of AI technologies, which require frameworks capable of accommodating real-time system evolution and adaptive learning (Kessler & Martin, n.d.; Xue et al., 2024). Practically, the results advocate for a multi-stakeholder approach: industry leaders must design phased training programs that prioritize operational skills; educators should revise curricula to balance technical and ethical skills; and policymakers need to bridge regional gaps through public-private partnerships and localized AI initiatives (Plikas et al., 2024; Rath et al., 2024).

The successful integration of AI in automobile manufacturing hinges on a delicate balance between technological advancement and human adaptability. By prioritizing foundational skills, addressing regional inequities, and embedding ethical considerations into AI strategies, stakeholders can unlock the full potential of these technologies, ensuring that workforces remain resilient, empowered, and prepared for the challenges of tomorrow.

9. Limitations

This study, while comprehensive in its exploration of workforce readiness for AI-driven automobile manufacturing, is subject to several limitations. A primary constraint arose during the data collection phase, which coincided with the Christmas holiday season. This timing significantly impacted the feasibility of conducting in depth interviews with respondents, as large number of expected participants were unavailable possibly due to holidays. Consequently, the reliance on a structured survey as the sole data collection method, while pragmatic under the circumstances, limited the depth of qualitative insights that could have been extracted through the interviews. The survey, though designed to capture a broad spectrum of perspectives, inherently restricts the ability to probe nuanced challenges or contextualize responses through follow up questions, potentially excluding essential information regarding regional or organizational differences.

Another limitation arises from the diversity of the surveyed population. The study targeted managers across diverse segments of the automobile industry, including luxury car manufacturers, military vehicle producers, electric vehicle (EV) companies, and budget-friendly automotive manufacturers. While this approach aimed to capture a holistic view of the sector, the inherent variability in technological adoption across these sub sectors introduced complexity. For instance, luxury and EV manufacturers often operate with cutting-edge AI systems, whereas budget-friendly or military vehicle producers may rely on different type of technologies with a completely different skilled workforce. This disparity in technological maturity across respondents" workplaces may Possess distorted ideas of "AI readiness," as interpretations of "advanced" systems differ significantly based on organizational setting.

Furthermore, the survey's extensive scope, which was intended to be inclusive, had the potential to dilute sector-specific insights by aggregating challenges that are unique to specialized markets (e.g., military vehicle safety protocols or EV battery production) into generalized findings. The limitations were further exacerbated by the geographical distribution of respondents. The sample size for certain regions, particularly underdeveloped areas, remained disproportionately small, despite efforts to assure representation from both developed and underdeveloped regions. For instance, the responses from African nations were scarce in comparison to those from Europe or North America, which may have resulted in an underrepresentation of the obstacles encountered by regions with restricted access to AI infrastructure or training resources. This imbalance may have inadvertently exacerbated preexisting biases in the literature, which frequently emphasizes perspectives from technologically advanced economies. In addition, the classification of nations into "developed" and "underdeveloped" categories, while essential for comparative analysis, oversimplifies the complex socio-economic and technological gradients within these regions. For example, emerging economies such as India or Brazil demonstrate pockets of sophisticated manufacturing in conjunction with persistent infrastructural gaps, a nuance that binary categorization is unable to capture. Additional constraints are introduced by the dependence on self-reported data from administrators. The responses were inherently subjective, reflecting the participants" perceptions of their workforce's skills rather than objective assessments of skill proficiency. The risk of social desirability bias is introduced by this, as managers may overstate their organizations" preparedness to align with industry trends or underreport gaps in order to avoid criticism. Additionally, the survey's emphasis on managerial perspectives resulted in the exclusion of direct input from factory workers, whose firsthand experiences with AI systems could have uncovered discrepancies between leadership assumptions and on-ground realities. For instance, a manager's assurance regarding the workforce's proficiency in operating cobots may not be entirely consistent with the actual comfort or competency levels of workers in their daily interactions with these systems.

Lastly, the study's capacity to monitor the development of workforce skills over time is restricted by its cross-sectional design. The adoption of AI in manufacturing is a dynamic process that is influenced by the changing demands of the market and the swift advancements in technology. The effectiveness of training programs in adapting to these shifts and the longitudinal changes in skill requirements are not accounted for by a snapshot analysis, as conducted here. This static perspective may fail to consider cyclical challenges, such as the delay between technological advancements and the corresponding upskilling of the workforce, which are essential for comprehending the sustainability of AI integration.

10. Future Research Directions

The rapid evolution of AI in manufacturing requires revaluation of existing frameworks so they better align with the adaptive and evolving nature of modern AI-driven systems. The Unified Theory of Acceptance and Use of Technology (UTAUT), while widely used to assess technology adoption, lacks the flexibility needed to account for AI's real-time learning and adaptability. Traditional constructs like performance expectancy and effort expectancy assume that technology remains static after implementation, but AI continuously evolves based on user interactions and new data. The study "Revisiting Unified Theory of Technology and Use of Technology Using Meta-analytic Structural Equation Modelling" suggests that an updated model, UTAUT-AI, could better capture these complexities by adding factors like adaptive trust, which looks at how user confidence in AI changes over time, and dynamic usability, which considers how AI interfaces evolve with worker proficiency (Or, 2023). Future research should focus on refining UTAUT-AI by incorporating ethical and psychological aspects, like how fears of job loss, algorithmic transparency, and data privacy concerns influence AI acceptance. Without these refinements, existing technology adoption models risk becoming outdated in the face of rapidly advancing AI systems.

Beyond theoretical improvements, long-term studies are needed to assess how AI integration impacts workforce dynamics over time. While this study identified regional skill gaps, future research should explore whether government-supported AI training programs and infrastructure investments help workers remain resilient in the long run. The study "The Role of Structured Training in Addressing Regional Skill Gaps for AI Adoption" highlights the importance of public-private collaborations in sustaining AI education (Patil, n.d.). Comparative cross-industry studies could also provide insights into how different sectors adopt AI, revealing best practices tailored for industries like automotive, aerospace, and small-scale manufacturing. While cobots are widely used in large-scale automotive factories, their adoption in small-batch production remains less studied. Research into how smaller industries modify AI applications to fit their unique workflows could help expand AI's practical use cases across multiple sectors.

The role of emerging technologies in AI training is another area worth exploring. The study "Artificial Intelligence Application and High-Performance Work Systems in the Manufacturing Sector" points out that augmented reality (AR) and virtual reality (VR) can provide hands-on training in AI-driven environments, offering a safe, immersive way for workers to learn AI-related tasks (Zahoor et al., 2024). But their scalability in underdeveloped regions where digital infrastructure is weak and is still unclear. Future research could look into how low-cost, offline-compatible AR/VR training modules could be designed to bring AI education to more resource-constrained environments. Additionally, the rise of micro-credentials and digital badges as AI skill certifications raises questions about how employers perceive these credentials in different industries and countries. The study "The Impact of Artificial Intelligence on Higher Education: An Empirical Study" suggests that digital certifications could help standardize AI training, but there's little research on whether they actually lead to better job opportunities (Slimi, 2023). Investigating how employers in various sectors evaluate AI-related certifications could help shape future training programs. Cultural and socio-economic influences on AI adoption also warrant deeper investigation. While this study found resistance to AI adoption in certain regions, the underlying reasons whether cultural beliefs, economic conditions, or lack of trust in technology are still not fully understood. Ethnographic research could explore how workplace cultures shape AI adoption behaviours, particularly in regions where resistance to automation is higher. The study "Global AI Policy and Standardization Trends" emphasizes the importance of aligning AI governance policies across countries, but achieving regulatory harmonization remains difficult due to differences in legal frameworks and workforce policies (De Almeida et al., 2021). Future research could examine ways to standardize AI regulations internationally so industries operating in multiple regions can adopt AI technologies more smoothly. Another key research area is algorithmic fairness in AI-powered manufacturing systems. Predictive maintenance, AI-driven hiring, and automated quality control all rely on algorithms that may inadvertently reinforce biases. Future studies should analyze how algorithmic bias affects worker opportunities and whether existing fairness models adequately address discrimination risks. The study "Addressing Ethical Challenges in AI Governance" highlights the importance of transparency, fairness, and accountability in AI systems (Wilczek et al., 2024). Research into bias detection models and fairness audits for AI applications in manufacturing could provide practical solutions for reducing bias and ensuring fair AI deployment across industries. Finally, the study "International Collaboration in AI Research and Development" highlights the role of cross-border AI research initiatives in addressing global disparities (Kseng, 2024). Establishing joint AI research hubs in emerging AI markets could help bridge knowledge gaps and make sure equal access to AI advancements. Additionally, shared funding mechanisms and open innovation platforms, as outlined in "Achieving Cross-Border Government Innovation", could help redistribute AI resources more fairly to regions that lack independent research skills (Oecd, 2021).

By focusing on improving theoretical models, assessing long-term workforce impacts, developing new training technologies, studying cultural influences, addressing AI fairness, and fostering global research collaborations, future research can provide practical solutions for making AI integration more inclusive, ethical, and effective. Addressing these areas will help make sure AI adoption is scalable, sustainable, and beneficial for industries and workers worldwide.

11. References

1. Amejwal, M., El Jaouhari, A., Arif, J., Fellaki, S., & Jawab, F. (2022). Production Flow Management Based on Industry 4.0 Technologies. *2022 14th International Colloquium of Logistics and Supply Chain Management (LOGISTIQUA)*, 1–7. https://doi.org/10.1109/LOGISTIQUA55056.2022.9938064

2. Arena, F., Collotta, M., Luca, L., Ruggieri, M., & Termine, F. G. (2021). Predictive Maintenance in the Automotive Sector: A Literature Review. *Mathematical and Computational Applications*, *27*(1), 2. https://doi.org/10.3390/mca27010002

3. Arents, J., Abolins, V., Judvaitis, J., Vismanis, O., Oraby, A., & Ozols, K. (2021). Human–Robot Collaboration Trends and Safety Aspects: A Systematic Review. *Journal of Sensor and Actuator Networks*, *10*(3), 48. https://doi.org/10.3390/jsan10030048

4. Babashahi, L., Barbosa, C. E., Lima, Y., Lyra, A., Salazar, H., Argôlo, M., Almeida, M. A. D., & Souza, J. M. D. (2024). AI in the Workplace: A Systematic Review of Skill Transformation in the Industry. *Administrative Sciences*, *14*(6), 127. https://doi.org/10.3390/admsci14060127

5. Bayaga, A., & Du Plessis, A. (2024). Ramifications of the Unified Theory of Acceptance and Use of Technology (UTAUT) among developing countries' higher education staffs. *Education and Information Technologies*, *29*(8), 9689–9714. https://doi.org/10.1007/s10639-023-12194-6

6. Benotsmane, R., Dudás, L., & Kovács, G. (2021). Survey on New Trends of Robotic Tools in the Automotive Industry. In K. Jármai & K. Voith (Eds.), *Vehicle and Automotive Engineering 3* (pp. 443–457). Springer Singapore. https://doi.org/10.1007/978-981-15-9529-5_38

7. Bosch, J., Olsson, H. H., & Crnkovic, I. (2018). *It Takes Three to Tango: Requirement, Outcome/data, and AI Driven Development*.

8. Bretones Cassoli, B., Hoffmann, F., & Metternich, J. (2021). *Comparison of AI-Based Business Models in Manufacturing: Case Studies on Predictive Maintenance*. https://doi.org/10.15488/11286

9. Chimeudeonwo, B. N. (n.d.). *REVIEW ON THE AI TECHNOLOGIES USED IN THE MANUFACTURING OF ELECTRIC CARS*.

10. Chryssolouris, G., Alexopoulos, K., & Arkouli, Z. (2023). Artificial Intelligence in Manufacturing Equipment, Automation, and Robots. In G. Chryssolouris, K. Alexopoulos, & Z. Arkouli, *A Perspective on Artificial Intelligence in Manufacturing* (Vol. 436, pp. 41–78). Springer International Publishing. https://doi.org/10.1007/978-3-031-21828-6_3

11. Cohen, Y., & Gal, H. C. (2024). Digital, Technological and AI Skills for Smart Production Work Environment. *IFAC-PapersOnLine*, *58*(19), 545–550. https://doi.org/10.1016/j.ifacol.2024.09.269

12. De Almeida, P. G. R., Dos Santos, C. D., & Farias, J. S. (2021). Artificial Intelligence Regulation: A framework for governance. *Ethics and Information Technology*, *23*(3), 505–525. https://doi.org/10.1007/s10676-021-09593-z

13. Demlehner, Q., Schoemer, D., & Laumer, S. (2021). How can artificial intelligence enhance car manufacturing? A Delphi study-based identification and assessment of general use cases. *International Journal of Information Management*, *58*, 102317. https://doi.org/10.1016/j.ijinfomgt.2021.102317

14. Dolgui, A., Haddou Benderbal, H., Sgarbossa, F., & Thevenin, S. (2024). Editorial for the special issue: AI and data-driven decisions in manufacturing. *Journal of Intelligent Manufacturing*, *35*(8), 3599–3604. https://doi.org/10.1007/s10845-024-02499-9

15. Dr. Aajaz Ahmad Hajam, & Alphonsa S John. (2024). *Reskilling and Upskilling Strategies in the Era of Automation: A Human-Centered Approach to Workforce Development*. https://doi.org/10.5281/ZENODO.13912971

16. Druml, N., Macher, G., Stolz, M., Armengaud, E., Watzenig, D., Steger, C., Herndl, T., Eckel, A., Ryabokon, A., Hoess, A., Kumar, S., Dimitrakopoulos, G., & Roedig, H. (2018). PRYSTINE - PRogrammable sYSTems for INtelligence in AutomobilEs. *2018 21st Euromicro Conference on Digital System Design (DSD)*, 618–626. https://doi.org/10.1109/DSD.2018.00107

17. Espina-Romero, L., Gutiérrez Hurtado, H., Ríos Parra, D., Vilchez Pirela, R. A., Talavera-Aguirre, R., & Ochoa-Díaz, A. (2024). Challenges and Opportunities in the Implementation of AI in Manufacturing: A Bibliometric Analysis. *Sci*, *6*(4), 60. https://doi.org/10.3390/sci6040060

18. Flick, D., Vruna, M., Bartos, M., Ji, L., Herrmann, C., & Thiede, S. (2023). Machine learning based internal and external energy assessment of automotive factories. *CIRP Annals*, *72*(1), 21–24. https://doi.org/10.1016/j.cirp.2023.04.038

19. Giordano, D., Giobergia, F., Pastor, E., La Macchia, A., Cerquitelli, T., Baralis, E., Mellia, M., & Tricarico, D. (2022). Data-driven strategies for predictive maintenance: Lesson learned from an automotive use case. *Computers in Industry*, *134*, 103554. https://doi.org/10.1016/j.compind.2021.103554

20. Gros, T. P., Gros, J., & Wolf, V. (2020). Real-Time Decision Making for a Car Manufacturing Process Using Deep Reinforcement Learning. *2020 Winter Simulation Conference (WSC)*, 3032–3044. https://doi.org/10.1109/WSC48552.2020.9383884

21. Hofmann, M., Neukart, F., & Bäck, T. (2017). *Artificial Intelligence and Data Science in the Automotive Industry*. https://doi.org/10.48550/ARXIV.1709.01989

22. Jain, M., & Kulkarni, P. (2022). Application of AI, IOT and ML for Business Transformation of The Automotive Sector. *2022 International Conference on Decision Aid Sciences and Applications (DASA)*, 1270–1275. https://doi.org/10.1109/DASA54658.2022.9765294

23. Jerry A. Madrid. (2023). The Role of Artificial Intelligence in Automotive Manufacturing and Design. *International Journal of Advanced Research in Science, Communication and Technology*, 795–802. https://doi.org/10.48175/IJARSCT-11959

24. Kaasinen, E., Anttila, A.-H., Heikkilä, P., Laarni, J., Koskinen, H., & Väätänen, A. (2022). Smooth and Resilient Human–Machine Teamwork as an Industry 5.0 Design Challenge. *Sustainability*, *14*(5), 2773. https://doi.org/10.3390/su14052773

25. Keleko, A. T., Kamsu-Foguem, B., Ngouna, R. H., & Tongne, A. (2022). Artificial intelligence and real-time predictive maintenance in industry 4.0: A bibliometric analysis. *AI and Ethics*, *2*(4), 553–577. https://doi.org/10.1007/s43681-021-00132-6

26. Kessler, S. K., & Martin, M. (n.d.). *How do potential users perceive the adoption of new technologies within the field of Artificial Intelligence and Internet-of-Things?*

27. Kseng, S. (2024). *International Collaboration in AI Research and Development*. *2*(1).

28. Lijffijt, J., Gkorou, D., Hertum, P. V., Ypma, A., Pechenizkiy, M., & Vanschoren, J. (n.d.). *Introduction to the Special Section on AI in Manufacturing: Current Trends and Challenges*.

29. Maclure, J., & Russell, S. (2021). AI for Humanity: The Global Challenges. In B. Braunschweig & M. Ghallab (Eds.), *Reflections on Artificial Intelligence for Humanity* (Vol. 12600, pp. 116–126). Springer International Publishing. https://doi.org/10.1007/978-3-030-69128-8_8

30. Madhavaram, C. R., Sunkara, J. R., Kuraku, C., Galla, E. P., & Gollangi, H. K. (2024). The Future of Automotive Manufacturing: Integrating AI, ML, and Generative AI for Next-Gen Automatic Cars. *IMRJR*, *1*(1). https://doi.org/10.17148/IMRJR.2024.010103

31. Makhado, M., & Sukdeo, N. (2018). *Advanced Manufacturing: The key to future competitiveness in the automotive industry*.

32. Malatji, W. R., Eck, R. V., & Zuva, T. (2020). Understanding the usage, Modifications, Limitations and Criticisms of Technology Acceptance Model (TAM). *Advances in Science, Technology and Engineering Systems Journal*, *5*(6), 113–117. https://doi.org/10.25046/aj050612

33. Matheson, E., Minto, R., Zampieri, E. G. G., Faccio, M., & Rosati, G. (2019). Human–Robot Collaboration in Manufacturing Applications: A Review. *Robotics*, *8*(4), 100. https://doi.org/10.3390/robotics8040100

34. Merhi, M. I., & Harfouche, A. (2024). Enablers of artificial intelligence adoption and implementation in production systems. *International Journal of Production Research*, *62*(15), 5457–5471. https://doi.org/10.1080/00207543.2023.2167014

35. Moniz, A. B., Candeias, M., & Boavida, N. (n.d.). *Changes in productivity and labour relations: Artificial intelligence in the automotive sector in Portugal*.

36. Mueller, C., & Mezhuyev, V. (2022). AI Models and Methods in Automotive Manufacturing: A Systematic Literature Review. In M. Al-Emran & K. Shaalan (Eds.), *Recent Innovations in Artificial Intelligence and Smart Applications* (Vol. 1061, pp. 1–25). Springer International Publishing. https://doi.org/10.1007/978-3-031-14748-7_1

37. Nyale, D., Karume, S., & Kipkebut, A. (2024). A comprehensive analysis of the role of artificial intelligence in aligning tertiary institutions academic programs to the emerging digital enterprise. *Education and Information Technologies*, *29*(17), 22407–22426. https://doi.org/10.1007/s10639-024-12743-7

38. Or, C. (2023). Revisiting Unified Theory of Technology and Use of Technology Using Meta-analytic Structural Equation Modelling. *International Journal of Technology in Education and Science*, *7*(1), 83–103. https://doi.org/10.46328/ijtes.420

39. Park, J. (2024). Analyzing the direct role of governmental organizations in artificial intelligence innovation. *The Journal of Technology Transfer*, *49*(2), 437–465. https://doi.org/10.1007/s10961-023-10048-4

40. Patil, D. (n.d.). *Impact of artificial intelligence on employment and workforce development: Risks, opportunities, and socioeconomic implications*.

41. Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2007). A Design Science Research Methodology for Information Systems Research. *Journal of Management Information Systems*, *24*(3), 45–77. https://doi.org/10.2753/MIS0742-1222240302

42. Plikas, J. H., Trakadas, P., & Kenourgios, D. (2024). Assessing the Ethical Implications of Artificial Intelligence (AI) and Machine Learning (ML) on Job Displacement Through Automation: A Critical Analysis of Their Impact on Society. In M. Farmanbar, M. Tzamtzi, A. K. Verma, & A. Chakravorty (Eds.), *Frontiers of Artificial Intelligence, Ethics, and Multidisciplinary Applications* (pp. 313–325). Springer Nature Singapore. https://doi.org/10.1007/978-981-99-9836-4_24

43. Plorin, D. (2022). AI Reshaping the Automotive Industry. In O. Vermesan, *Artificial Intelligence for Digitising Industry – Applications* (1st ed., pp. 3–9). River Publishers. https://doi.org/10.1201/9781003337232-2

44. Qiu, Y., Tang, Z., & Luo, Y. (2023). Cross-Border Technology Integration in the Field of Artificial Intelligence Based on Neural Network Algorithm. In A. Li, Y. Shi, & L. Xi (Eds.), *6GN for Future Wireless Networks* (Vol. 505, pp. 67–74). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-36014-5_7

45. Rath, S. P., Tripathy, R., & Jain, N. K. (2024). Assessing the Factors Influencing the Adoption of Generative Artificial Intelligence (GenAI) in the Manufacturing Sector. In S. K. Sharma, Y. K. Dwivedi, B. Metri, B. Lal, & A. Elbanna (Eds.), *Transfer, Diffusion and Adoption of Next-Generation Digital Technologies* (Vol. 697, pp. 115–128). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-50188-3_11

46. Selim, T. H., & Gad-El-Rab, M. (2024). Artificial Intelligence and the Global Automotive Industry. In T. Walker, S. Wendt, S. Goubran, & T. Schwartz (Eds.), *Artificial Intelligence for Sustainability* (pp. 31–53). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-49979-1_3

47. Sinha, S., & Lee, Y. M. (2024). Challenges with developing and deploying AI models and applications in industrial systems. *Discover Artificial Intelligence*, *4*(1), 55. https://doi.org/10.1007/s44163-024-00151-2

48. Slimi, Z. (2023). The Impact of Artificial Intelligence on Higher Education: An Empirical Study. *European Journal of Educational Sciences*, *10*(1). https://doi.org/10.19044/ejes.v10no1a17

49. Sonntag, M., Mehmann, J., & Teuteberg, F. (2021). *Application of Industry 4.0 in the automotive sector*. https://doi.org/10.15480/882.3989

50. Suhaib Kamran, S., Haleem, A., Bahl, S., Javaid, M., Prakash, C., & Budhhi, D. (2022). Artificial intelligence and advanced materials in automotive industry: Potential applications and perspectives. *Materials Today: Proceedings*, *62*, 4207–4214. https://doi.org/10.1016/j.matpr.2022.04.727

51. Sundaresan, S., & Zhang, Z. (2022). AI-enabled knowledge sharing and learning: Redesigning roles and processes. *International Journal of Organizational Analysis*, *30*(4), 983–999. https://doi.org/10.1108/IJOA-12-2020-2558

52. Tekic, Z., Cosic, I., & Katalinic, B. (2019). Manufacturing and the Rise of Artificial Intelligence: Innovation Challenges. In B. Katalinic (Ed.), *DAAAM Proceedings* (1st ed., Vol. 1, pp. 0192–0196). DAAAM International Vienna. https://doi.org/10.2507/30th.daaam.proceedings.025

53. Venkatesh, V. (2022). Adoption and use of AI tools: A research agenda grounded in UTAUT. *Annals of Operations Research*, *308*(1–2), 641–652. https://doi.org/10.1007/s10479-020-03918-9

54. Vermesan, O., John, R., Pype, P., Daalderop, G., Kriegel, K., Mitic, G., Lorentz, V., Bahr, R., Sand, H. E., Bockrath, S., & Waldhör, S. (2021). Automotive Intelligence Embedded in Electric Connected Autonomous and Shared Vehicles Technology for Sustainable Green Mobility. *Frontiers in Future Transportation*, *2*, 688482. https://doi.org/10.3389/ffutr.2021.688482

55. Wilczek, B., Thäsler-Kordonouri, S., & Eder, M. (2024). Government regulation or industry self-regulation of AI? Investigating the relationships between uncertainty avoidance, people's

AI risk perceptions, and their regulatory preferences in Europe. *AI & SOCIETY*. https://doi.org/10.1007/s00146-024-02138-0

56. Xue, L., Rashid, A. M., & Ouyang, S. (2024). The Unified Theory of Acceptance and Use of Technology (UTAUT) in Higher Education: A Systematic Review. *Sage Open*, *14*(1), 21582440241229570. https://doi.org/10.1177/21582440241229570

57. Zafar, M. H., Langås, E. F., & Sanfilippo, F. (2024). Exploring the synergies between collaborative robotics, digital twins, augmentation, and industry 5.0 for smart manufacturing: A state-of-the-art review. *Robotics and Computer-Integrated Manufacturing*, *89*, 102769. https://doi.org/10.1016/j.rcim.2024.102769

58. Zahoor, S., Chaudhry, I. S., Yang, S., & Ren, X. (2024). Artificial intelligence application and high-performance work systems in the manufacturing sector: A moderated-mediating model. *Artificial Intelligence Review*, *58*(1), 11. https://doi.org/10.1007/s10462-024-11013-9