Powering Up the Workforce

An Evaluation of Skill Assessment Methods for Battery Production Operators

Master's thesis in Production Engineering

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DEPARTMENT OF INDUSTRIAL AND MATERIALS SCIENCE

CHALMERS UNIVERSITY OF TECHNOLOGY
Gothenburg, Sweden 2025
www.chalmers.se

Master's thesis 2025

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Master's Thesis 2025
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Typeset in LaTeX
Printed by Chalmers Reproservice
Gothenburg, Sweden 2025

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Abstract

The growing battery industry faces an urgent need for skilled operators, driven by rapid technological development, industrial transformation, and workforce shortages. To support recruitment, training, and upskilling, reliable methods for assessing practical skills are essential—especially as future workers often come from diverse backgrounds. This thesis investigates how operator skills relevant to battery production can be effectively assessed.

A literature review identified seven categories of skill assessment methods: self-assessment, test-based, human observation, performance-based, computer-aided, AI-supported, and background-based assessments. An experimental study was conducted at Battery Center Gothenburg (BCG), using self-assessments, human expert observations, and performance-based assessments. The results show that each method captures different aspects of skill: self-assessments are scalable and promote reflection but are prone to bias; human expert observations provide contextual insight but require consistency and resources; and performance-based assessments offer objective measures of real task execution, though they are time- and resource-intensive.

The findings clarify how different assessment methods can support various stages of training and evaluation in the battery industry. By understanding their respective advantages and limitations, educators and companies can implement more targeted and effective strategies to assess and develop the skills needed to meet the sector's growing workforce demands.

Keywords: Battery Industry, Skills Assessment, Operator Training, Performance-Based Assessment, Human Expert Observation, Self-Assessment.

Acknowledgements

I would like to express my sincere gratitude to everyone who supported and contributed to the completion of this thesis.

To the participants, observers, and trainers at Battery Center Gothenburg, thank you for your engagement, time, and openness throughout the experimental phase. Your involvement was essential to the empirical part of this study.

To Greta Braun, my supervisor at Chalmers, thank you for your thoughtful guidance and valuable insights throughout the project. Your support helped shape both the direction and depth of this work. With your encouragement, the work felt meaningful and purposeful.

I would also like to thank Johan Bengtsson and Daniel Nåfors at Göteborgs Tekniska College for generously sharing your perspectives in our discussions, and for contributing with practical knowledge, experience, and the opportunity to carry out this project.

I would like to express my sincere gratitude to Professor Johan Stahre, the examiner of this thesis, for his formal academic role and for his valuable support throughout the process.

Lastly, I am deeply grateful to my friends and family for their patience, encouragement, and continuous support along the way.

Ida Wackerberg, Gothenburg, June 2025

Declaration of Use of AI

This report was written with the help from different AI tools. The AI tools used were Grammarly and ChatGPT. Grammarly was used to ensure correct spelling and grammar throughout the report. ChatGPT was used to refine certain sentences for clarity, ensuring the message could be easily understood by the reader. All text and information have been created by me, Ida Wackerberg, before applying any AI tools for improvement.

List of Acronyms

Below is the list of acronyms that have been used throughout this thesis listed in alphabetical order:

Acronym	Full Term
AI	Artificial Intelligence
ALBATTS	Alliance for Battery Technology, Training and Skills
AR	Augmented Reality
BCG	Battery Center Gothenburg
BES	Battery Energy Storage
BMS	Battery Management System
BVC	Battery Value Chain
EBA	European Battery Alliance
EVs	Electric Vehicles
EOL	End-of-line
GHG	Greenhouse Gases
HMI	Human Machine Interface
Li-ion	Lithium-ion
OTJ	On-the-Job
PLO	Power Lock Out
PPE	Personal Protective Equipment
SD	Standard Deviation
UNI	University
USS	Upper Secondary School
VET	Vocational Education and Training
VR	Virtual Reality

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1
Introduction

The industrial sector has undergone several transformative phases, commonly referred to as industrial revolutions. From mechanization (Industry 1.0) and mass production (Industry 2.0) to automation (Industry 3.0) and digitalization (Industry 4.0), each phase has introduced new technologies that reshaped production processes and workforce demands[1, 2]. The ongoing transition toward Industry 5.0 emphasizes collaboration between humans and advanced technologies, creating new challenges and opportunities for skill development[2].

Moreover, new subsectors are emerging as industries transform, such as the rapidly growing battery industry. Many industries are undergoing significant changes, setting new requirements for employees who must continuously adapt. This study focuses on the increasing demand for skilled workers within the battery value chain and is conducted in collaboration with Göteborgs Tekniska College at Battery Center Gothenburg, an educational center dedicated to developing skills for the battery industry[3].

1.1 Background

The urgency of addressing climate challenges is becoming prominent. In 2016, the Paris Agreement became legally binding and today 195 parties have signed off, including the European Union[4]. In the agreement, all parties have agreed that by 2050, emissions need to become net zero. In Europe, the transportation sector stands for a quarter of the greenhouse gases (GHG) meaning there is a large potential for decarbonization efforts[5]. During COP26, companies in the automotive industry, cities, and other stakeholders announced their commitment to transitioning to zero-emission vehicles[6].

To realize the vision regarding zero-emission vehicles, automotive companies have significantly invested in battery electric vehicles (BEVs)[7, 8]. Therefore, numerous gigafactories have been built in Europe to meet the growing demand for large-scale battery production. However, this rapidly expanding industry faces a critical challenge: a shortage of trained and experienced personnel[7].

The battery industry is predicted to create 10 million jobs related to the entire value chain[8]. In Europe, 800,000 people will need to be upskilled, reskilled, and trained to manage the shortage of adequate workers by the end of 2025[9]. The European

Parliament has dedicated resources to develop education and materials on how to realize this. Moreover, the European Battery Alliance (EBA) has been formed to strengthen the industry[10]. EBA consists of different stakeholders in the battery value chain such as national authorities, regions, and research institutes with the purpose of creating a sustainable battery value chain.

The European Commission has created a set of 20 principles representing the social rights in the union[11]. One of these pillars, Education, training and life-long learning, emphasizes that every individual should have the opportunity to acquire new knowledge and skills throughout their life. This principle aims to support individuals in adapting and transitioning to the changes in an evolving labor market[11].

1.2 Purpose and Goals

The shortage of staff with the appropriate skills presents a significant challenge for industries, particularly in sectors experiencing rapid transformation. As technological development accelerates, the need for continuous upskilling and reskilling becomes critical. Given the diverse educational and professional backgrounds of these individuals, there is a growing need to map their current skill levels in a structured and reliable way. This thesis focuses on exploring and evaluating methods for assessing the skills of individuals who may work as operators in battery production. Accurately assessing skills is essential for individuals, employers, and education providers to make informed decisions about training and workforce development. However, there is limited guidance on how skill assessment should be carried out in this context, and how different methods may reflect varying perspectives on skills.

1.3 Research question

To structure the investigation and support a systematic approach to the topic, a set of research questions was developed. These questions aim to clarify how different assessment methods can be applied to evaluate operator skills, and how they offer varying insights depending on context and perspective. Together, they frame the scope and direction of the study.

- How can skills for operators in the battery industry be assessed effectively?
  - How do various assessment methods reflect different perspectives on skill evaluation?
  - In which contexts are specific skill assessment methods most appropriate for evaluating skills in the battery industry?

1.4 Delimitation

The primary focus of this thesis is to evaluate skill assessments methods to map the skills of potential employees for the battery industry. Some aspects of this study will concentrate specifically on battery production, while other parts will have applicability across industries. Practical tests will be done on BCG, meaning that potential empirical studies will be limited to testing skills using the equipment available at the facility. The scope of this study is specifically focused on operators in battery production facilities.

2
Battery Center Gothenburg

BCG is a competence and learning center focused on preparing the future workforce for roles in battery production. It functions as both a learning factory (see Section 3.3.1) and a collaborative competence hub, bringing together education providers, industry stakeholders, and employees to support skills development. The experimental study took place at Battery Center Gothenburg. BCG is an initiative that is a collaboration between the City of Göteborg, Business Region Gothenburg, the Region of Göteborg, and the Region Västra Götaland. The operational lead is Göteborgs Tekniska College.[3].

BCG educates and spreads knowledge through customized training modules. During training and education, participants engage in hands-on practice that mirrors real production scenarios. The training modules are based on what the participant needs, there are modules connected to electrical safety, automated and standardized work, battery electrode manufacturing, and high-automated battery production. The modules have different names, and the ones that are of focus in this thesis are what are referred to as Skill Training and Scenario-based Industrial Training, which are described in the following sections.

2.1 Skill training

Skill training focuses on electrode manufacturing, cell assembly, and cell finishing. The education consist of giving the participants a theoretical background of the production, a brief introduction to the equipment, and then a practical exercise. The practical exercise consist of different stations. The participants are split into pairs, where one pair performs tasks on one station. The stations that groups can be stationed at are: Slurry Mixing, Coating, Calendering, Slitting, Stacking, Cell Assembly, and Cell Finishing. The practical tasks are carried out in an environment that mirrors reality, but on a small scale, utilizing non-hazardous materials. For example the mixing stations is done with the help of a household mixer when in reality the mixers used in an industrial setting can handle hundreds of liters. In this thesis project, 4 stations were used to measure skills. These stations were Slurry Mixing, Calendering, Slitting and Cell Finishing.

Slurry Mixing is the first step in electrode production. Participants prepare a homogeneous slurry—comprising active material, conductive additive, binder, and solvent—using a household mixer. They then perform quality checks for viscosity, density, dry-matter content, particle size, and pH, using a viscosity meter, precision scale, moisture analyzer, pH-meter, micropipette, and grindometer. The personal protective equipment for this station includes an apron, gloves, and safety goggles.

In Calendering, the participants press a laminated “electrode” sample through manual rollers to achieve uniform coating thickness and minimise porosity. After pre-pressing, they measure thickness at marked points with a micrometer and inspect quality, such as surface defects, under a microscope. Clay, a rolling pin, scraper, scale, a pasta machine, and a microscope serve as analogues for industrial equipment. The personal protective equipment for this station includes an apron, gloves, and safety goggles.

Slitting mimics the separation of large electrode rolls into daughter rolls. Participants use a paper guillotine to cut analog sheets to specific measurements, then verify daughter-roll width and corner angles with a ruler and protractor. They inspect the cut edges for burrs—irregular metal shards—under a microscope. Personal protective equipment includes gloves and glasses.

Cell Finishing represents the final stage: formation, ageing, and end-of-line testing. Using a 9 V battery, participants first verify that the multimeter is calibrated, then measure open-circuit voltage on two assembled “cells.” They visually inspect for swelling, cracks, or leaks, perform a thickness check to detect swelling, and log results in an end-of-line QC protocol. PPE includes gloves and safety goggles.

2.2 Scenario-based Industrial Training

During scenario-based industrial training, the participants get to interact with a simulated automated production cell. The simulation replicates the real plant’s workflow in which coated lithium-ion cells arrive via conveyor, the cells are prepared and placed on endplates for subsequent stacking and battery-pack assembly. The participants interact with the training equipment in the following way:

- **Production screen**: Shows the simulated production line with its robot stations, conveyor belts, and sensor checkpoints in real time.
- **Human Machine Interface, HMI**: Reveals the health of the cell’s equipment—e.g. whether any station has broken down or is operating correctly. The operators also request access to the cell through the HMI.
- **Status screen**: Displays live upstream and downstream line conditions, indicating how the production flow is progressing before and after the cell.
- **Andon button**: Enables operators to request assistance from teamleaders, trainers, mirroring the shop-floor escalation protocol.
- **Safety-gate interlock**: When the participants want to interact with equipment in the production cell, there is a protocol and safety gate to follow to get access. Once the satey-gate is opened, all production immediately stops and can not be restarted until the gate is closed.

The participants receive a briefing and demonstration of how the equipment works, including safety systems, etc. They are then given the opportunity to interact with the equipment independently, troubleshoot simulated faults, and familiarize themselves with the interface, controls, and standard workflows. The participants do this for approximately 10 minutes before moving on to the real work sessions. During a full education, the participants are introduced to new concepts following a work session. In a full training cycle, new concepts are introduced between sessions, this study focuses on the first session, which emphasizes corrective maintenance. Later sessions address other concepts such as preventive maintenance, quality systems, and buffer strategies.

The first work session lasts for 20 minutes and is focused on corrective maintenance. The production runs, and at regular intervals faults occur, simulating wear on the system. When a fault appears, it is indicated on the HMI; participants must locate the correct component in their instructions, request access, install a power lock out, PLO, lock, and enter the cell. A PLO lock is a critical safety mechanism designed to prevent the safety gate from being closed and the production from restarting while someone is physically inside the cell. This lockout ensures that maintenance tasks are performed under safe conditions, reflecting real-world industry protocols for high-automation environments.

As soon as they open the gate, the HMI panel goes blank, simulating that the participants have physically moved inside the cell. Participants then follow the standardized corrective maintenance procedure they found earlier in their instructions—entering various fault-code sequences. When they believe the fault is corrected, they “exit” the cell, meaning they remove the PLO lock and close the door. Once they have exited the cell, the HMI shows if the problem was correctly fixed; if not, the participants have to redo the corrective maintenance procedure. Once the problem is fixed, the participant needs to perform a reset and acknowledge the entrance to the cell, per industry standard. The final step is to restart production.

Once production restarts, the simulation continues to manufacture parts. After a set runtime — again simulating component wear — participants must address a new fault. This cycle repeats until 20 minutes have elapsed. The number of faults depends on the uptime corresponding to component wear, up to a maximum of eight faults. When the 20 minutes are up, the total output from that production cell is presented.

Trainers serve as team leaders and are called on each time a group resolves a fault to record data on what corrective maintenance a pair has performed. However, the trainers remain active throughout the work session, answering questions but also monitoring for safety breaches or risky behavior.

3

Theoretical Framework

This chapter outlines the theoretical framework of the thesis, encompassing an overview of battery technology and production, the evolving skills and competencies needed in the battery industry, approaches to upskilling and learning environments, as well as psychological factors influencing learning outcomes.

3.1 The Battery Industry

The need for efficient energy storage is growing, and batteries are the dominant technology for this purpose[12]. Batteries are used across a wide range of applications, including portable consumer electronics, healthcare devices, industrial systems, and automotive products [13].

Batteries play a crucial role in achieving the targets set by the Paris Agreement, becoming climate-neutral by 2050[14]. Batteries enable energy storage from renewable energy sources, such as solar and wind power[14]. Additionally, batteries are a key technology in the electrification of the transportation sector, supporting the shift from fossil fuels to electric vehicles. The growing demand for batteries has created a need for large-scale battery production to meet the needs of these sectors[15].

The Battery Value Chain, BVC, spans from raw material extraction to recycling and reuse, encompassing various stages such as material processing, cell and pack manufacturing, integration into end-use applications, and end-of-life management[16]. Each stage requires distinct processes, technologies, and workforce competencies.

3.1.1 Battery Technology Overview

Batteries are electrochemical cells that store chemical energy, and through electrochemical reactions, the energy can be converted into electrical energy[17]. An electrochemical cell has two electrodes, an anode and a cathode, which are placed in an electrolyte filling.

The chemical reactions involved are oxidation and reduction. Oxidation occurs at the anode, where electrons are released, while reduction takes place at the cathode, where electrons are gained[18]. When connected to a component through an external circuit, the electrons flow from the anode to the cathode, generating an electric current. At the same time, ions migrate through the electrolyte to balance the charge and complete the internal circuit. A separator is placed in the electrolyte between the two electrodes to prevent a short circuit and enable the exchange of ions. A simplified overview of a battery cell can be seen in Figure 3.1.

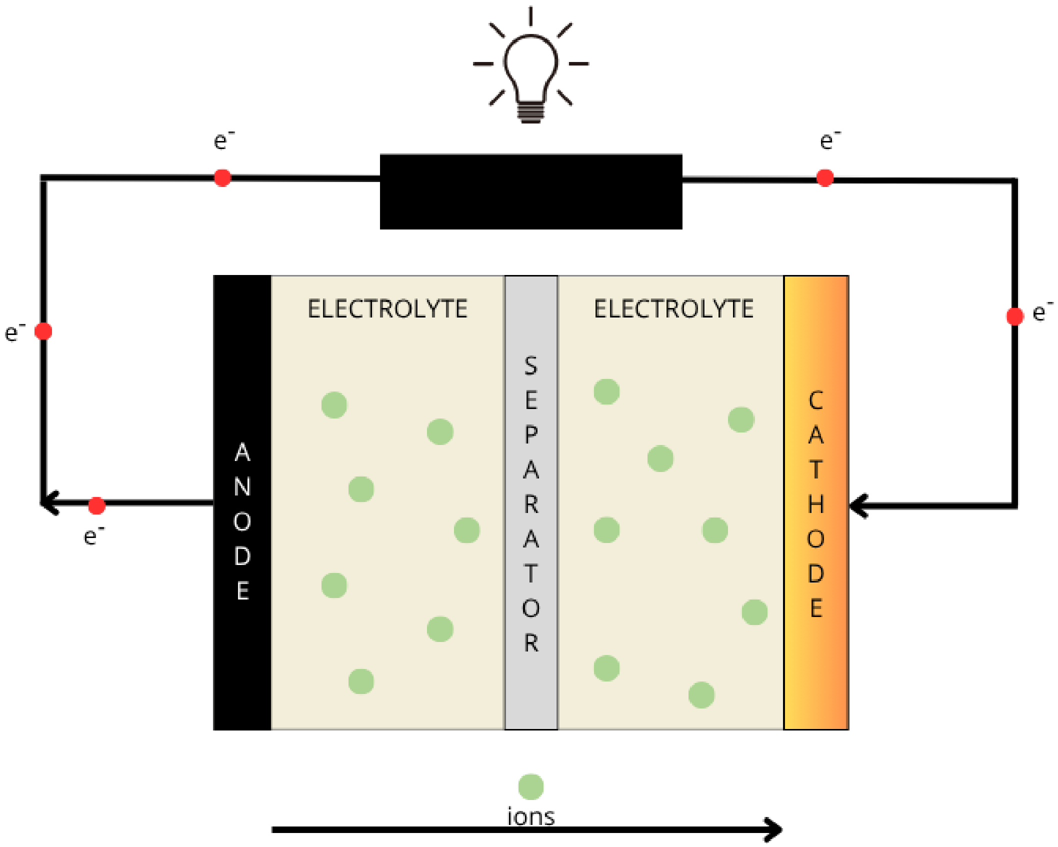

Figure 3.1: Overview Battery

Many batteries also have current collectors that acts as a conductor between the electrodes and the external circuit[19]. Additionally, they serve as a substrate supporting the active material of the electrodes.

There are multiple types of batteries intended for different applications. Some characteristics of the batteries are the material, structure, and if they are classified as primary or secondary[18, 20, 21]. If a battery is classified as primary, the chemical reaction can only occur once, meaning that it is not possible to recharge the battery. Batteries that are classified as secondary can be recharged, and the chemical reaction is then reversed.

Primary batteries are commonly used in household electronics. For example, alkaline batteries are frequently found in devices such as flashlights [20]. Lithium metal batteries, which are more compact, are often used in small devices like watches.

One secondary battery type is lithium-ion batteries, which are commonly used in the automotive industry[18].

3.1.1.1 Lithium-ion Batteries

Lithium-ion, Li-ion, battery, cells are commonly built in three different shapes, cylindrical, prismatic - hard-case, prismatic - pouch[22]. All cell shapes contain the same essential components: anode, cathode, electrolyte filling, current collectors, and separator. However, the different formats offer various advantages depending on factors such as cost, production complexity, and mechanical stability[22].

Li-ion batteries are widely applicable and range from smartphones, computers, electric vehicles, EVs. The versatility of Li-ion batteries and the high energy density is one of the reasons why the market for rechargeable Li-ion is prominent[23].

The material and structure of the battery decides the characteristics, and in a Li-ion battery, the most commonly used material for the anode is graphite and lithium alloyed metals[23]. The cathode typically consists of various metal oxides [24]. The current collector for the anode is usually constructed from copper, while the cathode collector is made from aluminum. Both the anode and cathode active materials are typically processed into a mixture, which is then coated onto their respective current collectors[24].

3.1.2 Battery Production

Battery production can be divided into five main stages: extraction of raw materials, electrode manufacturing, cell assembly, cell finishing. and battery pack manufacturing[25]. A battery pack consists of multiple battery cells, with each cell created from electrodes made of different materials. In Figure 3.2, an overview of the production process is shown, not including inactive steps such as drying. While the overall structure of cell assembly is similar across formats, specific steps and methods differ depending on the cell type. The following section describes the process based on a prismatic hard-case cell.

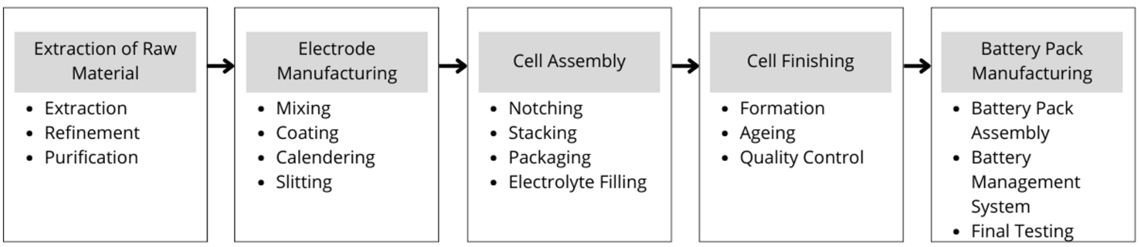

Figure 3.2: Battery production process.

3.1.2.1 Extraction of raw material

The first step involves the extraction of raw materials, followed by their refinement and purification. The extraction of critical materials such as lithium, cobalt, and nickel is geographically concentrated in a few regions around the world[26]. This process can have significant environmental impacts, including the release of CO_2 emissions, water contamination, and disruption of local ecosystems and wildlife[25]. After extraction, the raw materials undergo processing to achieve the purity levels required for battery applications[25].

3.1.2.2 Electrode Manufacturing

When the materials have been processed, the electrodes can be manufactured. The active materials, which form the functional part of the electrodes, are typically prepared into a mixture, what is referred to as a slurry. The slurry consists not only of the active material but also additives such as binders and conductors[27, 28]. Quality features of the slurry are for example homogeneity and viscosity[27]. The slurry is then coated onto both sides of the current collectors — aluminum foil for cathodes and copper foil for anodes. As the slurry is wet the foils need to go through a drying process before the next step. The drying process consist of multiple ovens heated at different temperatures for avoidance of thermal damages[27, 28].

The dried foils then pass through a calendering process where the material gets compressed to reduce thickness and increase conductivity[28]. The electrodes are often referred to as mother rolls, which can be subsequently split into smaller units known as daughter rolls in a process step called slitting[27, 28]. Before assembly into a cell, the electrodes typically require an additional drying step to remove any remaining moisture[27].

3.1.2.3 Cell Assembly

Cell assembly consists of multiple steps, beginning with notching/separation. In this step the daughter rolls are cut into single electrodes. The electrodes and separator layers are then stacked on each other in the following order: anode, separator, cathode, separator. Depending on cell configurations, one cell stack can contain over 100 layers[27, 28].

The next step is packaging, where the collectors are welded together, and then the cell stack is inserted into the battery cell housing. The housing is then sealed, often using laser welding[27]. After packaging, the electrolyte is filled into the cell under controlled conditions, and the final sealing step is performed to fully enclose the cell[27].

3.1.2.4 Cell finishing

Cell finishing consists of three main steps: formation, aging, and quality control. During formation, the battery cell is charged and discharged for the first time in a special rack, where it is connected through spring-loaded contact pins. The cell is then monitored over a longer period by measuring the open circuit voltage to discover the self-discharge rate and potential short circuits[27].

Before leaving the factory, the cells undergo several quality control tests to classify and sort them based on their performance and quality. The battery cells are placed in an end-of-line, EOL, testing rig, where they are discharged and undergo a series of tests to ensure they meet the specification[27, 28].

The cell finishing process is a very time- and space-consuming part of cell production. All cells must be individually charged, discharged, and tested under controlled conditions, which requires specialized equipment and significant factory floor space[28]. Additionally, the formation and aging steps can take several days.

3.1.2.5 Battery Pack Manufacturing

In many applications, individual battery cells are grouped together to form a battery pack in a casing. The cells are assembled into a module/pack where they are connected either in series or parallel with the help of busbars, enabling the electrical circuit to pass through multiple cells[25].

When the cells are connected a Battery management system, BMS, is installed to monitor the battery during usage. The BMS makes sure that all cells work within safe regions. After this is installed, the battery pack undergoes additional quality checks and tests[25].

3.2 Skills and Competency Needs

Skills are, according to the European Union, the capacity to utilize knowledge and practical experience to perform tasks and address problems[29]. As the industrial sector evolves with new technology due to environmental, economic and social challenges new requirements for industrial workers are created. Companies are dependent on having skilled employees, and in the manufacturing sector, a skilled workforce is considered one of the most important competitive factors[30].

Skills can generally be divided into hard and soft skills. Hard skills refer to technical abilities and the capacity to translate knowledge into practical tasks and measurable outcomes[31]. Soft skills are interpersonal, intrapersonal, and socio-emotional abilities that enable individuals to manage themselves and interact effectively with others[31]. However, skills are complex and often interrelated. In [32], an alternative framework for categorizing and labeling skills is introduced, dividing skills into five distinct areas: Knowledge, Active Cognition, Conation, Affection, and Sensory-Motor Abilities. The framework highlights that skills may be associated with multiple categories simultaneously, reflecting a more complex nature of skills.

3.2.1 Skill Gaps and Challenges

The industrial sector has undergone a major transformation, from mechanical craftsmanship to automated and advanced manufacturing systems[1]. To leverage the effectiveness of automated and advanced manufacturing systems in the era of the 5th industrial revolution humans and machines need to work together[33]. Additionally, the available workforce is shrinking due to the demographic shift, creating a workforce shortage[34, 35].

Skill gaps can be defined in various ways, but they generally refer to the mismatch between the skills available in the workforce and the skills required by employers. According to [36], a skill gap appears when there is difficulty in finding an employee with the correct skills at the correct time to meet organizational and market demands. This definition is synthesized from multiple sources in the literature. Similarly, [37] defines skill gaps as the difference between the skills an employee currently possesses and the skills they need to effectively perform their work.

In comparison between sectors, manufacturing is where skill gaps are the most common[37]. To address skill gaps, bridge gaps, the core factor for companies is to acknowledge and analyze their need for certain skills. The most common ways to bridge the skill gaps are training, recruitment, relocating work tasks, outsourcing, or discontinuation of these specific operations[37]. However, due to ongoing demographic changes—such as an aging workforce and a shrinking labor pool—recruitment alone is becoming increasingly difficult[38]. As a result, upskilling the existing workforce is not only more feasible but also essential to ensure long-term competence supply and adaptability in industry[38].

Upskilling refers to the process of enhancing existing skills to meet the evolving demands of a current role or to qualify for a related role, while still building on an individual's existing skill base [39]. Reskilling, on the contrary, involves acquiring entirely new skills[39]. It is estimated that around 20 million currently employed workers in Europe will need to be reskilled into new occupations by 2030. Highlighting the urgent need for educational institutions and training providers addressing these skill gaps[40].

[36] states that there is no commonly applied or standardized method for mapping skill gaps. However, the article highlights that self-assessment is one of the most frequently used approaches. In [38], self-evaluations are described as a tool that enables individuals, particularly students—to become aware of changes occurring within the industry and to plan their learning accordingly.

3.2.2 Skills in the Manufacturing Sector

The manufacturing sector faces ongoing challenges in attracting and retaining skilled employees[41]. The continued growth of the industry, especially under the influence of technological advancements, has increased the demand for workers at all levels, including highly skilled production workers[41]. A primary driver of this demand is the sector's transition toward Industry 4.0 and 5.0. Specifically, workers must possess a blend of technical manufacturing skills, digital skills, and soft skills to operate effectively in increasingly complex production environments[41].

While automation and advanced technologies have transformed the production environment, human operators remain central to manufacturing. Digital tools can enhance operators' performance, but they cannot replace the flexibility, creativity, and problem-solving abilities of people. As highlighted by [42], operators are still essential, even in smart manufacturing systems. Their ability to respond to change and find solutions in uncertain situations is what makes them irreplaceable.

At the same time, the demand for cognitive skills continues to grow as production systems become more digital and automated[34, 35]. Workers in the manufacturing industry often have repetitive tasks, but analysis shows that they have a high need for education and training to meet the demand for the future industry[43]. Operators are predicted to be highly influenced by new standards and changes to increase productivity and sustainability. Technologies like robotics, digital twins, and AI will affect plant operators' day-to-day work[43]. Operators, are expected to acquire new skills, including the ability to analyze digital information, manage and maintain automated machinery, and utilize digital systems that enable data-driven decisions[44]. Furthermore, social skills, problem-solving, and critical thinking are also stated to be important skills for operators in the manufacturing sector.

3.2.3 Skill Requirements in the Battery Industry

The battery industry sees a growing demand, creating new requirements for the employees working within the battery production[44]. Along the BVC, there is a workforce shortage, and the most critical skill gaps lie in areas such as electrochemistry, battery chemistry, battery management systems, product and system design, manufacturing processes, and safety practices[45]. Operators are expected to manage complex, automated machinery, adhere to strict quality and safety protocols, and possess specific knowledge related to materials handling[45]. As the BVC evolves, these roles increasingly demand a combination of technical, digital, and collaborative skills to ensure high production efficiency and product quality.

Defining the explicit skills that are needed in the battery industry has been done as a master's thesis at BCG in 2024[46]. Skills have also been defined through ALBATTS (Alliance for Battery Technology, Training and Skills), which maps workforce skills across the entire BVC through skill cards for different occupations[47]. The skills identified in [46], along with those presented in the operator-related skill cards[48, 49], were condensed into the unified list presented in Table 3.1.

Table 3.1: List of Defined Skills for Battery Operators

Skill Abbrev	Full Skill Name
S1	Collaboration, Communication, and Teamwork
S2	Curiosity and Lifelong Learning
S3	Applying and Following Standardized Work Methods
S4	Following Work Instructions and Recipes
S5	Using Personal Protective Equipment (PPE)
S6	Accuracy and Focus
S7	Conducting Product Sampling
S8	Detecting Defective Products
S9	Documentation and Monitoring of Production Data
S10	Handling Sensitive Materials, Equipment, and Products
S11	Thinking Sequentially
S12	Troubleshooting and Problem Solving
S13	Calculating and Understanding Key Metrics and Parameters
S14	Equipment Maintenance
S15	Using and Operating Machines

3.3 Upskilling Initiatives and Learning Environments

This section describes different training approaches in industry and some of the formats used to build skills, especially in contexts where rapid upskilling or reskilling is required. This section also outlines some key policy and institutional initiatives that aim to support workforce development and align training efforts with broader economic and technological transitions.

3.3.1 Training Approaches in Industry

There are different approaches to train potential and current workers in industrial settings. These approaches vary in structure, delivery method, and purpose, ranging from informal, experience-based learning to highly structured programs.

On-the-job (OTJ) training, where workers are educated and trained at their workplace is one approach[50]. This can involve learning how to perform specific tasks tied to a particular role or gaining broader experience in general tasks relevant across different settings. OTJ training typically occurs under the supervision of more experienced colleagues and allows learners to develop practical skills while contributing to ongoing production[50].

A simulated environment, where the trainee practices in either a physical replica, digital application, or virtual environment, is another common approach to industrial training[51]. A simulated training environment removes the risk of impacting the actual production process and allows for mistakes. It also increases training accessibility and efficiency, allowing participants to repeat tasks, receive objective feedback, and prepare before entering real production environments[51].

A concept referred to as learning factories involves simulations of real industrial environments, where participants are educated through hands-on practice and real task performance[52]. These environments allow trainees to perform, experiment, and test their skills in a controlled and realistic setting. Learning factories can be designed for a range of purposes, including education, workforce training, and applied research, and they may take different forms. In their most traditional format, they provide hands-on, physical access to actual production systems. However, other versions can include virtual simulations or support remote interaction, broadening accessibility while preserving industrial relevance[52].

3.3.2 Policy and Institutional Initiatives

Several initiatives at both the EU and national levels aim to accelerate workforce adaptation in response to green and digital transitions. These efforts focus on equipping workers with the necessary competencies to meet evolving industrial demands, including the growing need for skills in battery manufacturing, automation, and sustainable technologies.

The European Battery Alliance (EBA) is one of these initiatives, which was launched by the European Commission to gather researchers, national authorities, and stakeholders along the BVC[53]. Its goal is to lay the groundwork for a competitive and sustainable battery cell manufacturing industry in Europe[54].

One key partner to EBA is InnoEnergy, which played a central role in coordinating the alliance's early industrial development roadmap[54]. This work included bringing together over 120 stakeholders from across the battery value chain to identify the actions needed to build a robust European battery ecosystem. Continuing, InnoEnergy later established the InnoEnergy Skills Institute (formerly the European Battery Academy), which focuses on equipping current and future workers with the technical and transversal skills required in battery manufacturing and related industries[55, 56].

3.4 Psychological Factors in Learning Environments

In training and educational environments, there are multiple factors affecting the learning process and individual performance. Psychological factors include motivation, self-efficacy, self-perception, psychological safety.

3.4.1 The Johari Window and Self-Perception

The Johari window is a methodology for visualizing that there are multiple perceptions of who people are. The model is structured as a square divided into four quadrants, each representing different aspects of self-awareness and perception[57]. The first quadrant represents the open area, the aspects that are known to both the individual and their surroundings. The second quadrant represents the blind spot, the area that the surrounding people see but not the individual. The third quadrant is the hidden area which represents what only the individual knows. Finally, the fourth quadrant represent what no one knows.

The Johari window is an important model to understand when talking about self-awareness and perception. There are things that an individual does not know while it's surrounding does and the other way around. In [58] it is promoted as a model to utilize when talking about personal growth. It is stated as a way to understand your weaknesses and strengths from another perspective.

The Dunning-Kruger Effect is what can be referred to as the more you know, the less you know[59]. The phenomenon concludes that individuals with low competence in an area are more likely to overestimate their abilities in the same area then compared to people with more competence. This occurs because those with limited skills often lack the metacognitive ability to accurately evaluate their performance[59]. In contrast, more competent individuals are generally more aware of the complexity of the domain and their own limitations[60]. As a result, individuals with greater expertise may underestimate their own abilities.

3.4.2 Self-Efficacy and Motivation

The perception of what you know can be influenced by self-efficacy. Self-efficacy is defined as an individual's belief in their capacity to execute specific tasks or achieve goals[61]. An individual's belief affects how they approach challenges. According to [61], if an individual have high self-efficacy they are more likely to invest more effort and time when approaching a task in the same area. When having high self-efficacy the motivation is also said to be higher[61].

The development of self-efficacy is influenced by several key factors, including background, gender, age, past experiences, social feedback, and emotional states. According to [61], there are four sources of self-efficacy: personal experience and success, experience gained through observing others, positive feedback from others, and the emotional state of the individual when faced with the task. The impact of gender, age and task related area has been studied. In [62] the gender differences in academic self-efficacy was analyzed. It was found that males tend to report higher self-efficacy than females in mathematics and computer-related domains, while females report slightly higher self-efficacy in language-related tasks. The study also highlighted that age and context-specific factors interferes when shaping self-efficancy.

The impact of gender are evident in fields which are male-dominated according to [63]. In male dominated fields women report lower self-efficacy compared to males, even in cases where the performance have been assessed to be similar[63]. It is also highlighted that this disparity is largely influenced by societal norms and gendered expectations, which shape how individuals assess their own competence. In [63], the disparity was demonstrated through a self-assessment task, where participants were asked to rate their ability to succeed in a given activity. This pattern is further supported by [64], who emphasize that self-efficacy is shaped by chronic self-views, individuals have about their own capabilities. The study shows that these chronic self-views, built on societal norms and gendered expectations, affect how individuals estimate their performance.

3.4.3 Psychological Safety and Learning Transfer

Psychological safety refers to when an individual feel confident to express themselves, make mistakes, ask questions without being judged by others[65]. In a learning environment having psychological safety allows the participants to feel confident in taking risks, seek feedback and engage in the activity. The perceived severity of the consequence also impacts the feeling of psychological safety[65]. When the stakes are low—for example, when errors are reversible or part of the learning process, participants are more likely to experiment and take risks. In contrast, when the potential consequences of a mistake are high, such as damaging equipment or being embarrassed, individuals may become more hesitant and reserved.

In addition to psychological safety, there are other factors that affect how well learning is transferred from training to real-world settings. [66] defines three categories influencing learning transfer: teacher characteristics, training design , and work environment. Psychological safety falls within the third category, as it reflects the social and cultural context in which learning takes place. However, effective transfer also depends on learner motivation, cognitive ability, self-efficacy, and the alignment of training content with real work tasks[66]. Within the category of training design and delivery, the execution of the training itself is emphasized. Aspects such as structure, sequencing, instructional methods, and the degree of realism embedded in the training environment are considered critical for enabling transfer.

4

Methodology

The methodology was split into three phases, starting with an analysis of existing methods to assess skills, followed by an experimental study, and concluding with an analysis of the collected data (see Figure 4.1). The methodology was deployed to gain insight into what methods can be used for skill assessment, how different methods perform in practice, and how they reflect various perspectives on evaluating skills.

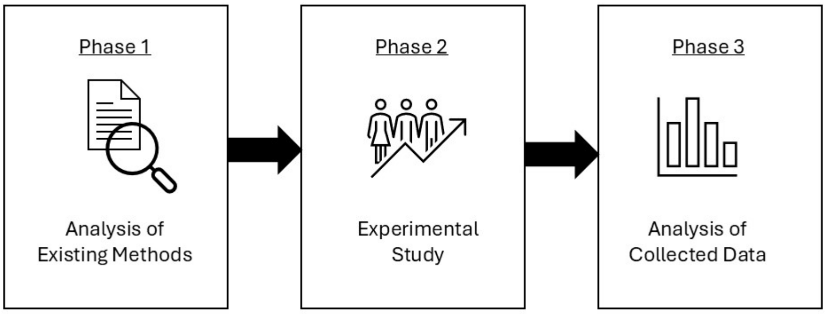

Figure 4.1: Phases of methodology

4.1 Analysis of Existing Assessment Methods

The methodology for reviewing existing skill assessment methods combined a systematic literature review with supplemental searches through broader online resources. The review was conducted following the guidelines on multivocal literature review presented in [67]. This method was chosen because it enables the use of different sources, both formal and informal. The steps are according to the guidelines, the following: Search, Source Selection, Quality Assessment, Data Extraction, Data Synthesis.

The search process was conducted to find formal and informal sources on skill assessment methods. The first part of the search was to define the search strings and search platforms. Additionally, this method involved using key articles or reports as a starting point and exploring their references and subsequent citing articles to expand the search[68]. For informal sources retrieved through search engines, the process was exploratory and iterative. After reviewing approximately eight pages of Google search results, the search reached a point of saturation, where additional pages no longer yielded new methods or meaningful insights.

The second step is source selection, where the potential sources are selected based on the specified selection criteria. This process entailed the following inclusion and exclusion criteria:

1. **Relevance to Skill Assessment Methods**
   Sources must discuss or describe methods, tools, or frameworks for assessing skills in any context (e.g., education, workforce, industry).
2. **Language:** Only sources written in English are included.
3. **Accessibility:** Full-text access to the source must be available.
4. **Publication Date:** Sources published from 2010 onwards are included to ensure recency, unless they are foundational or highly cited.
5. **Novelty of Context or Content:** Sources must present additional or distinct contextual information, methodological features, or application settings. If a method is already included and the source offers no new insight, it is excluded.

A total of 24 sources were selected after applying the inclusion and exclusion criteria. These comprised both academic literature and grey literature, including industry reports, organizational white papers, and public policy documents. The academic sources included peer-reviewed studies such as [69–85], while the grey literature consisted of documents from professional organizations and public bodies such as [86–91]. All selected sources were systematically reviewed and included in the data extraction and synthesis phases. See Table 4.1 for the search strings, platforms, and number of selected articles.

Table 4.1: Search strings and corresponding search platforms

Search String	**Search Platforms**	**Hits**	**Selected**
"Measuring skills"	Web of Science	48	6
"Measuring skills"	Google	301 000	4
"Skill Assessment"	Web of Science	104	11
"Skill Assessment"	Google	1 910 000	3

The third step was the quality assessment of the selected sources. Since informal sources differ significantly from formal academic literature. This step was particularly important for evaluating the reliability and relevance of non-academic materials. The quality assessment checklist used in this project was partly based on the framework presented in [67], but it was adapted to fit this study. The main adaptations were that the checklist was simplified to focus on core criteria, and that quality assessment was not used to exclude sources. Instead, quality-related dimensions were recorded as notes to inform the synthesis and interpretation of findings. See Appendix A for the full quality assurance checklist.

The fourth step in the framework presented in [67] is data extraction. This step was adapted and simplified to a version appropriate for a single-researcher review. A data extraction spreadsheet was designed to structure the findings of available skill assessment methods. See Table 4.2 for the template used.

Table 4.2: Template of data extraction table

Resource	**Ref.**	**Literature Type**	**Findings**	**Quality Note**

The final step of the review process involved synthesizing the extracted data to identify patterns, trends, and differences across assessment methods. The findings were grouped into categories based on methodological characteristics. Given that inclusion was based on novelty of context or approach, the synthesis focused on descriptive insights. This approach enabled a structured overview of the diversity in how skills are assessed. In Appendix C the data extraction form covering the 24 selected articles (18 peer-reviewed articles, 6 grey literature sources) with coded findings is available.

4.2 Experimental Study

The experimental study was conducted at Battery Center Gothenburg (BCG) during sessions where groups attended for educational purposes. The training program lasted between 3 to 5 days, depending on the group. While the main content remained the same across all groups, some components were extended for those attending the 5-day sessions.

The experimental study consisted of three phases. It began with an initial self-evaluation, where participants provided background information, including previous work and educational experience, and rated their own skill levels. This was followed by a practical assessment phase, during which participants performed hands-on tasks in a simulated industrial environment. Their performance was closely observed and evaluated by educators at BCG, who graded participants based on predefined criteria. These assessments were carried out at the start of each training program to establish participants' initial skill levels, prior to engaging in the core instructional content delivered at BCG.

After completing the training program at BCG, participants conducted a final self-evaluation to reflect on their progress and skills development.

4.2.1 Initial Self-Evaluation

The initial self-evaluation was conducted through a digital questionnaire in which each participant rated themselves on a Likert scale, indicating the extent to which they agreed with statements about their performance in specific skills. To provide additional context, each skill was broken down into several sub-questions, guiding participants on what the skill encompassed. The use of Likert scales for assessing subjective perceptions is a well-established method and was chosen due to its ease of converting subjective responses into quantitative data [92, 93].

The questionnaire was pilot-tested on four individuals before deployment. Two of the participants had no prior industrial experience, while the other two had previous experience in the manufacturing industry. Among the testers, one had completed a vocational education and was currently working as a maintenance technician. Two others held engineering degrees, and the fourth participant had a law degree. The selected test persons were chosen based on their different experiences and educational backgrounds to obtain multiple perspectives. As a result of the pilot test, two questions were revised — one was rephrased for clarity, and another was removed due to redundancy.

To enable traceability for a participant through all assessments - the self-assessed skills, skills demonstrated during practical exercises, and the self-assessed skills after completing education- the participant's name was collected. Moreover, the questionnaire contained questions addressing personal data, such as educational history, work-life experience, age, and gender. See Appendix B for the English version of the questionnaire. During the case study, all participants answered a Swedish version of the same form, and in total, 56 people answered the initial self-evaluation.

In terms of employment status, 19 participants reported being employed full-time. A large portion of the group were students, with 23 identifying solely as students, 11 combining studies with part-time work, and 2 combining studies with full-time work. This means that a total of 36 participants were engaged in some form of education, while 32 participants were either working full-time or studying alongside work.

Educational backgrounds varied, though most participants had completed or were studying some form of post-secondary education. The largest groups reported voca-

tional higher education, 23 participants, or upper secondary education, 22 participants, while 8 had attended university. Three participants selected "Other" as their highest level of education, and none reported only primary education.
The participants who completed the questionnaire represented a broad age range. Most respondents were between 18 and 44 years old, with the largest proportion (46%) falling within the 25–34 age group. Participants aged 18–24 made up 25% of the sample, while those aged 35–44 accounted for 18%. The smallest age groups included individuals aged 45–54 (9%), and one participant who was 55 years or older. In terms of gender, the group was predominantly male (68%), while women accounted for 30% of respondents. One participant identified as non-binary. To protect participant anonymity, demographic results are presented only in aggregate form. In addition to demographic data, participants were categorized based on their previous work experience. As shown in Figure 4.2, the majority (43 participants) reported backgrounds in manufacturing and industry. Other common sectors included retail and service, and transport and logistics, while smaller groups had experience in fields such as healthcare, construction, and public administration. Participants were able to indicate multiple relevant sectors, reflecting their background.

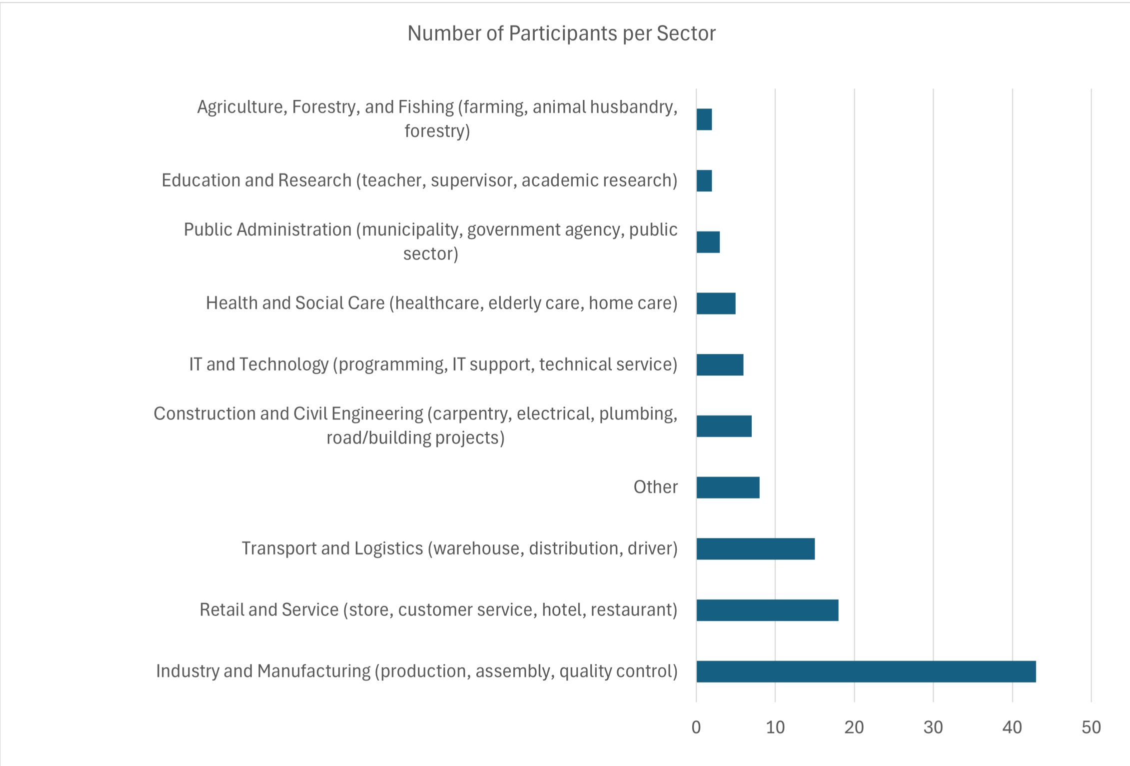

Figure 4.2: Participants grouped based on work experience

4.2.2 Observation and Trainers' Evaluation

The practical training included in the experimental study were: scenario-based industrial training and skills training. In the scenario-based industrial training, participants practiced interacting with a simulated automated robot cell, while the skills training allowed them to manually perform various steps of the "raw to cell" process. These different training setups aimed to develop key skills needed to become an operator in the battery industry. During the practical tasks, participants first received an introduction to the procedures and then attempted to carry them out themselves, with support available as needed. They worked in pairs and were encouraged to ask for assistance when necessary. A subset of participants was closely observed by independent observers who assessed their performance. In addition, the educators and trainers who guided the participants throughout the practical tasks also graded their performance. While the trainers provided assistance and supervision to the entire group, each trainer was primarily responsible for overseeing and supporting between one and three pairs of participants, depending on the setup.

4.2.2.1 Observations

The observations were performed on both the scenario-based industrial training and skill training. To record the wanted data, the format was a structured observation. A structured observation was seen as suitable as it allowed for quantitative data to be collected, and novice observers could be used[94]. This method depends on a consistent setup of the task being observed; since the practical tasks were always performed according to a standardized methodology, the observation protocols were developed to reflect this consistency.

In the scenario-based industrial training, the observation protocols focused on collecting timestamps, tracking the time it took participants to complete specific tasks. Additionally, the protocols recorded whether the group executed each task correctly on the first attempt and noted any safety-related errors. All participants followed the same task sequence during scenario-based industrial training; however, variation arose in how far each group progressed, with some completing more steps within the available time than others. Data was collected from 32 people when interacting with the equipment during scenario-based industrial training.

The skill training also utilized structured observation protocols; however, the setup differed from the scenario-based industrial training because participants were assigned to different stations. Consequently, four distinct protocols were developed: one focused on the slurry mixing station, one for the calendering station, one for the slitting station, and one for the station representing cell finishing. In this part of the experimental study, 4 protocols covering 8 participants were recorded at the slurry mixing station, 6 protocols covering 12 participants at the calendering station, 3 protocols covering 6 participants at the slitting station, and 6 protocols covering 12 participants at the cell finishing station. The protocols for the skill training were not based on timestamps but on a checklist covering yes and no questions.

In addition to the checklist- and timestamp-based protocols, the observers were also asked to monitor whether any significant misunderstandings occurred during the tasks. They recorded whether problems arose, whether participants attempted to solve these issues independently before seeking assistance, and how many times help was requested. Observers were also given the opportunity to provide free-text comments on the participants they observed, allowing for additional qualitative insights beyond the structured data. In total, 47 people were observed, and 22 of these were observed in both practical trainings.

The protocols used for the observations can be found in Appendix D.

4.2.2.2 Trainers' Evaluation

While observers focused on one pair at a time, the trainers focused on helping and educating the group. When the participants had performed their tasks, the trainer also evaluated the participants' performance in relation to a subset of skills. The trainer filled in a form for the participants they'd worked with and assessed their skills on a Likert scale, ranging from strongly disagree, disagree, neither agree nor disagree, agree, and strongly agree. In addition to these options, trainers could also select I don't know if they were unable to assess a particular skill. The forms were adapted to match the skills involved for the different practical tasks. Meaning, one trainer evaluation form was created for the scenario-based industrial training, while another one was created for skill training.

The trainers' evaluation represents an expert review of the participants' skills. See Appendix E for the form the trainers used to assess skills.

4.2.3 Final Self-Evaluation

When completing the training, participants were asked to fill in a self-evaluation once again. The purpose of this second self-evaluation, conducted through a digital questionnaire, like the first, was to gain insight into how participants' perceptions of their skills had changed over the course of the training. The questionnaire included the same questions as the initial self-evaluation, with the exception of questions 3, 4, and 20–24, which addressed personal data.

4.3 Analysis of Collected Data

The data was analyzed from the perspective of transforming the data into knowledge using the framework presented in [95]. This framework outlines five key steps for ensuring that data is meaningfully processed and prepared for interpretation:

- **Contextualized:** The purpose for which the data were gathered is clearly understood.
- **Categorized:** The data are organized into units of analysis or key components.
- **Calculated:** The data have been mathematically or statistically analyzed.
- **Corrected:** Errors or inconsistencies within the data have been identified and removed.
- **Condensed:** The data have been summarized or presented in a more concise form.

4.3.1 Self-evaluation Data

The data from the self-evaluations regarding perceived skill levels were processed in the same way for both questionnaires. The self-evaluation data were analyzed within the context of the key skills identified as essential for becoming an operator. The primary purpose of collecting this data was to measure how participants perceived their own skill level and skill development over time and to assess any shifts in confidence or competency perception resulting from the training. The answers were categorized by participant and skill, grouping the guiding sub-questions according to the specific skill each sub-question addressed. To generate a single metric for each skill, the responses to the associated sub-questions were averaged. Having a single metric for each skill allowed for comparison between different assessment methods. The two self-evaluations generated two separate datasets: one representing the initial self-evaluation and the other representing the evaluation completed after completing the education.

4.3.2 Trainers' Evaluation Data

The data from the trainers' evaluations were handled in a similar manner to the self-evaluation data. Questions addressing the same skills were grouped, with responses averaged to produce a single metric per skill. If a participant had data from both practical tasks, scores were averaged across setups. Some questions assessed the same skill across both setups, while others within a single setup covered multiple aspects of a skill. If data were missing from one setup or if a trainer had filled in "I don't know", only the available score was used for that participant in the overall mean calculation. If no data was available for a certain skill, it was left empty. The trainers' evaluations resulted in the creation of an additional dataset, which was organized and categorized by participant and skill. Notably, Equipment Maintenance (S14) was not observed for any participants, as it was not included in the practical tasks.

4.3.3 Observational Data

The observational data consisted of three types of data, depending on what protocol the data originated from:

- Timestamps
- Yes/No checklist
- Comments from observers

The timestamps were processed by calculating the time it took each group to complete different steps of the tasks in scenario-based industrial training. These time differences were then analyzed using the five-number summary (minimum, first quartile (Q1), median, third quartile (Q3), and maximum). This analysis allowed for categorization of groups as slow, average, or fast. Specifically, if a group was faster than Q3, they were categorized as fast; if they fell between Q1 and Q3, they were considered average; and if they were slower than Q1, they were categorized as slow.

Each subtask was mapped to the specific skills required to perform it, enabling the performance data to be linked directly to relevant skill areas. If a group performed these tasks efficiently —categorized as fast — this was interpreted as a positive indicator of proficiency in the associated skills.

In addition, a Yes/No checklist was used to record whether tasks were performed correctly on the first attempt. These results were mapped to the relevant skills associated with each subtask. Safety errors were also tracked and correlated with compliance with safety regulations and the ability to follow instructions.

For all subtasks linked to specific skills, participants were consistently assigned a score of +1, 0, or –1, based either on their performance relative to the group's timing distribution or, where applicable, on the group's correctness in executing the task.

In the Skill Training protocols, no timestamps were recorded; only checklists were used to verify whether participants performed the subtasks correctly. These subtasks were also mapped to different skills, and depending on whether the group performed them correctly or not throughout the practical session, they were assigned a score of +1, 0, or –1.

In both practical trainings, the observers were also required to comment on whether significant misunderstandings arose, whether the group encountered any problems, whether they attempted to resolve issues by themselves, and whether they asked for help. These were then also mapped to skills such as communication and teamwork, problem-solving, and troubleshooting.

Observers also had the opportunity to provide additional comments on aspects not captured by the structured protocols or to offer explanations for situations that required further context. These comments were processed using the methodology outlined in [96]. The methodology involves systematic steps for analyzing qualitative data and identifying patterns and insights. The first step involved thoroughly reading all comments multiple times to become familiar with the data. Initial codes were then constructed to capture meaningful comments and relevant observations. These codes were examined, and themes were identified. The resulting themes were named and linked to specific skills. When explicit comments clearly associated positive or negative assessments with particular skills, these were also assigned scores of +1, 0, or –1.

Finally, each participant was assigned an overall score for each skill by calculating the average of their scores across all available data from the observations. However, no data was collected in regard to Curiosity and Lifelong Learning (S2), Calculating and Understand- ing Key Metrics and Parameters (S13) and Using and Operating Machines (S15). The complete results were then compiled into a single dataset representing the observational assessment.

4.3.4 Triangulation of Data

The purpose of this triangulated analysis was to evaluate the consistency and divergence between different assessment methods, gain insight into perceived versus demonstrated competence, and identify how each method reflects participants' actual skill levels. This approach supports the aim of assessing the effectiveness and appropriateness of various skill evaluation methods within the battery industry context.

The above-mentioned methodologies resulted in four unique datasets. Each represents different perspectives on participants' skill levels: self-perception from self-evaluations, expert assessment from trainers' evaluations, and observed performance from structured observations. To analyze these datasets in relation to one another and to identify underlying patterns, an integrated analysis was conducted.

The first step of analyzing the data was to ensure the structure of the datasets were the same, including phrasing of skills and format of data. The observational dataset ranged from -1 to 1, but for the analysis, it was normalized to the same scale (1-5) as the other datasets. After this, the datasets were merged based on participants to enable the possibility to compare across methods. No participants were excluded due to missing data, missing values were handled by retaining blanks to reflect the true structure of available data.

The data were analyzed using descriptive and comparative methods. Descriptive methods, including mean scores and standard deviations, were calculated for each skill category within each dataset to provide an overview of performance and self-assessment patterns.

The first comparison aimed to explore changes over time. Paired comparisons between the initial and final self-evaluations were conducted to identify changes in perceived skill levels, see Figure 4.3.

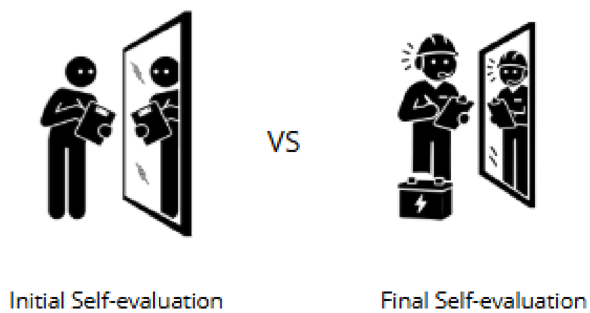

Figure 4.3: Triangulation of Data – Comparison 1

The second comparison aimed to evaluate the consistency between different assessment methods used to establish participants' initial skill levels, see Figure 4.4.

Figure 4.4: Triangulation of Data - Comparison 2

For deeper insight, the datasets were further enriched by incorporating demographic metadata, including age, gender, education level, and prior work experience which was collected during the initial questionnaire. This was done to reveal underlying patterns and to identify potential correlations between background factors and performance across the different assessment methods.

5

Results

This chapter presents the results from the analysis of existing assessment methods, the experimental study, and the data analysis.

5.1 Review of Skills Assessment Methods

The synthesis of reviewed sources revealed a broad spectrum of skill assessment methods used across professional and educational contexts. Seven sources applied the methods explicitly in the medical field, additionally, another one was pointed out as especially suitable for surgeries. The remaining sources applied assessment methods across a range of settings, including vocational education and training, corporate learning, policy and statistical frameworks, digital self-assessment tools, and evaluations of language or communication skills.

After categorization across settings, a total of seven distinct categories of assessment methods were identified: self-assessment, test-based, human observation, performance-based, computer-aided, AI-supported, and background-based assessment. Visualizations for all methods can be seen in Figure 5.1

Figure 5.1: Visualizations of the identified skill assessment methods

Self-assessments are based on the person's own perception of their skills and interests. In the findings, available in Appendix C, self-assessments are presented as a method that can be scalable and affordable, but also subjective[74]. The applications for self-assessment ranges from measuring skills to identifying gaps, possible career paths, or developing opportunities[72, 73, 89, 90, 97]. Test-based assessments were commonly used to measure theoretical knowledge or specific competencies through standardized formats such as multiple-choice tests, pre/post-training quizzes, or certification exams[86–88]. These methods appeared in both educational and corporate contexts and were often used to establish skill levels, either on a basic level or after an education.

Human observations are used in contexts where skills are evaluated by experts, managers, or peers, typically through rubrics, checklists, or rating scales, either live or through video recordings [80, 81, 83]. These observations can take the form of formal evaluations by trained assessors or more informal assessments by supervisors or colleagues in the workplace. Human observations were stated to be subjective, however that could be controlled by utilizing multiple observers[76, 79]. Human observations were stated to be costly and time-consuming[74, 76]. To contrast the human observations performance based assessments can be carried out. Performance-based assessments focus primarily on the outcome of a task rather than the observer's interpretation. These assessments rely on predefined metrics and objective criteria to evaluate how well a participant completes a specific task or demonstrates a skill[79, 86]. The performance based assessment can be incorporated to daily tasks[87].

Computer-aided assessments use digital solutions such as simulations or interactive platforms to evaluate skills in structured and often automated ways. These methods allow for the collection of objective performance data—such as task efficiency or accuracy—especially in vocational and medical settings [71, 78]. They are distinct from test-based assessments in that they simulate real-world tasks and track behavior rather than relying solely on standardized questions. While effective for skill-based evaluations, they may face limitations related to technology access and transferability to real-world performance[69].

AI-supported assessments leverage artificial intelligence to evaluate skills through automated analysis of behavior, performance data, or sensor inputs. The AI-assessment methods are stated to be less bias and scalable[76, 77, 85]. AI can analyze video, motion, or biometric data to provide objective and scalable feedback [76, 77]. Unlike computer-aided assessments that follow predefined metrics, AI systems adaptively interpret complex patterns, offering real-time insights without the need for continuous expert supervision [85]. AI-supported assessments were described as scalable and less prone to bias, but concerns were raised about the transparency of algorithms and the need for robust validation in applied contexts [85].

In some cases, personal background data, such as educational history, prior work experiences, or documented training, is used to determine what skills a person has[69, 87, 88, 91]. Additionally, self-reported work tasks can also be a part of deciding what skills a person has. These approaches are grouped under background-based assessment, as they rely on pre-existing personal and contextual information rather than direct testing or observation. While such methods can be efficient and scalable, they have been criticized for potentially failing to capture actual, current skill levels[88].

It is possible to combine methods when assessing skills, referred to as mixed methods or multidimensional evaluation[83, 88]. However, this was not included as a separate category in this review, as it represents a combination of existing methods. All reviewed assessment methods are summarized and described in Table 5.1.

Table 5.1: Skills Assessment Literature Overview

Category	**Assessment Method**	**Examples (with sources)**	**Notes**
Self-assessment	Self-reporting of skills, interests, or competence levels through surveys or digital tools.	Europass Digital Skills Tool [90]; National Careers Service quiz [89]; graduate self-assessments [74]; self-evaluation in active learning [73]; self in digital humanities [97].	Scalable and affordable; subjective due to self-perception; often used in early career guidance or self-directed learning.
Test-based assessment	Standardized tests or quizzes to measure cognitive or domain-specific knowledge.	DigComp factual assessments [90]; pre/post knowledge tests [87]; training certifications [86]; international skills surveys [88].	Objective and repeatable; common in formal education and corporate training; may not capture applied skills.
Human observation	Observation of task performance by experts, peers, or managers using rubrics or checklists.	Speaking skill assessment [80]; surgical observation tools [81]; peer/manager reviews [72]; dental evaluations [83].	Context-sensitive and flexible; subject to bias unless multiple observers used [76, 79]; resource-intensive [74].
Performance-based assessment	Evaluation through demonstration of real-world tasks or simulated procedures.	VETASSESS hands-on tests [91]; surgical suturing [78]; serious games [82]; embedded work tasks [87].	Focused on observable output; useful in vocational and medical training; metrics include accuracy, time, or error rate.

Continued on next page

Table 5.1: Skills Assessment Literature Overview (Continued)

Computer-aided assessment	Simulations or digital interfaces to assess task completion and behavior.	VR mastoidectomy training [84]; business simulations [71]; online platforms with mapping and gap analysis [72]; self-reflection tools [73].	Structured and scalable; reduces observer bias; requires access to digital infrastructure [69].
AI-supported assessment	Use of artificial intelligence and sensors to interpret performance and generate feedback.	AI surgical skill evaluation using video, kinematics, or eye tracking [76, 77]; automated systems in professional training [85].	Highly scalable and potentially unbiased; still under development; transparency and validation needed.
Background-based assessment	Skills inferred from educational history, prior experience, or documented tasks.	Eurostat indirect measures [88]; VETASSESS background/document review [91]; self-reported job tasks [69]; employer surveys [70]; AIR case studies [87].	Efficient and accessible; may not reflect current competence; often used in policy and certification contexts.

5.2 Self-Evaluation Result

To assess participants' perceived skills, self-evaluation data were collected before and after the training period using a standardized Likert-scale questionnaire. A total of 56 participants completed the initial self-evaluation, and 39 completed the final self-evaluation. Overall, participants reported high perceived competence at the start.

Median scores for most skills exceeded 4, indicating a high skill level. Skills related to safety, teamwork, and routines tended to receive consistently high ratings. Technical or task-related skills showed greater variation in responses.

Figure 5.2 presents a boxplot visualization of initial self-evaluation scores across all 15 skills, labeled S1 through S15. The figure shows both the average self-ratings and how much the scores varied between participants. Some skills have a wider spread of scores and more low outliers, which means that while many participants felt confident, others did not perceive their skill-level as high.

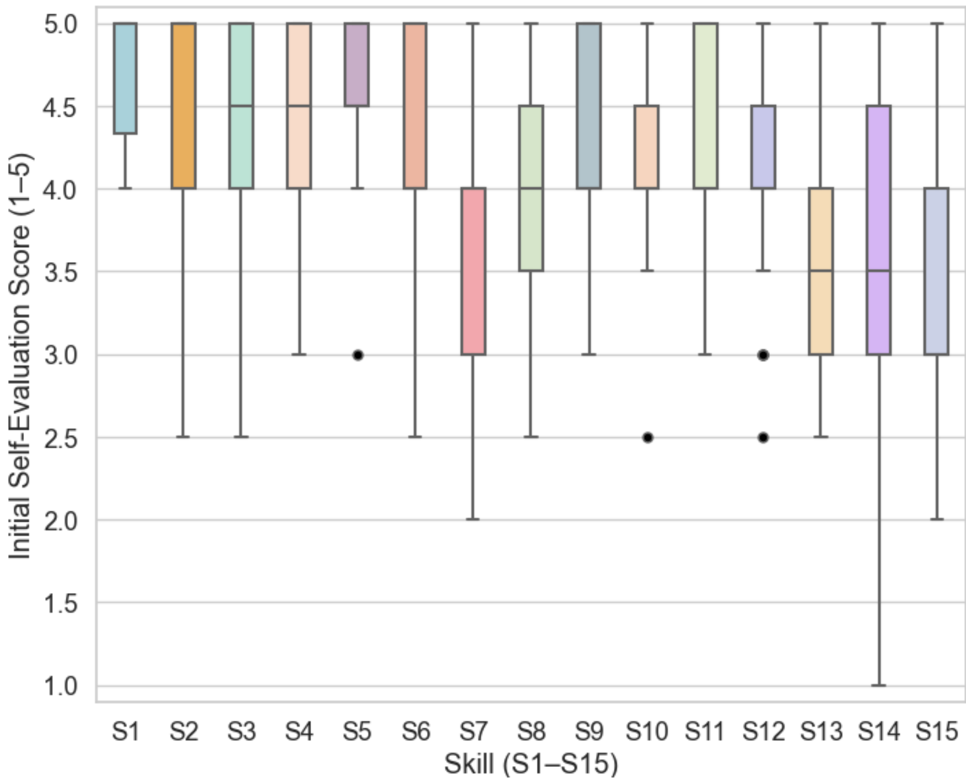

Figure 5.2: Initial self-evaluation scores across S1 to S15. Boxes show the interquartile range with medians marked; outliers are displayed as points.

Final self-evaluation scores remained high across most skills. In general, participants rated themselves slightly higher after the training, especially in skills the participants had rated themselves the lowest on the initial questionnaire. The most notable improvements were seen in Using and Operating Machines (S15), Conducting Product Sampling (S7), and Calculating and Understanding Key Metrics and Parameters (S13). The difference between initial and final self-evaluations are presented in Table 5.2.

Table 5.2: Average self-evaluation scores before and after training

Skill	Skill Name	Initial Mean ± SD	Final Mean ± SD
S1	Collaboration, Communication, and Teamwork	4.5 ± 0.5	4.6 ± 0.4
S2	Curiosity and Lifelong Learning	4.5 ± 0.6	4.6 ± 0.5
S3	Applying and Following Standardized Work Methods	4.3 ± 1.0	4.6 ± 0.4
S4	Following Work Instructions and Recipes	4.4 ± 0.6	4.5 ± 0.5
S5	Using Personal Protective Equipment (PPE)	4.4 ± 0.8	4.7 ± 0.5
S6	Accuracy and Focus	4.3 ± 0.6	4.4 ± 0.5
S7	Conducting Product Sampling	3.5 ± 1.0	4.3 ± 0.7
S8	Detecting Defective Products	4.0 ± 0.8	4.4 ± 0.6
S9	Documentation and Monitoring of Production Data	4.1 ± 0.8	4.4 ± 0.6
S10	Handling Sensitive Materials, Equipment, and Products	4.1 ± 0.7	4.4 ± 0.6
S11	Thinking Sequentially	4.2 ± 0.8	4.5 ± 0.6
S12	Troubleshooting and Problem Solving	4.1 ± 0.7	4.5 ± 0.5
S13	Calculating and Understanding Key Metrics and Parameters	3.7 ± 0.8	4.2 ± 0.6
S14	Equipment Maintenance	3.4 ± 1.1	4.2 ± 0.6
S15	Using and Operating Machines	3.4 ± 1.0	4.4 ± 0.7

5.3 Trainer Evaluation Results

A total of 53 participants were evaluated by trainers, who also serve as educators at BCG. However, not all participants received evaluations at every station, resulting in some variation in the number of assessments per skill. The results, summarized as mean scores with standard deviations, are presented in Table 5.3. The lowest average score was recorded for Following Work Instructions and Recipes (S4) and Using Personal Protective Equipment (PPE) (S5), while the highest scores were observed in Documentation and Monitoring of Production Data (S9), Thinking Sequentially (S11), Detecting Defective Products (S8) and Calculating and Understanding Key Metrics and Parameters (S13).

Table 5.3: Average trainer evaluation scores with standard deviation

Skill	Skill Name	Trainer Mean ± SD
S1	Collaboration, Communication, and Teamwork	3.9 ± 0.8
S2	Curiosity and Lifelong Learning	3.7 ± 0.8
S3	Applying and Following Standardized Work Methods	3.7 ± 0.6
S4	Following Work Instructions and Recipes	3.2 ± 1.1
S5	Using Personal Protective Equipment (PPE)	3.4 ± 0.8
S6	Accuracy and Focus	4.0 ± 0.9
S7	Conducting Product Sampling	3.8 ± 0.4
S8	Detecting Defective Products	4.1 ± 0.4
S9	Documentation and Monitoring of Production Data	4.4 ± 0.5
S10	Handling Sensitive Materials, Equipment, and Products	4.0 ± 0.2
S11	Thinking Sequentially	4.2 ± 0.4
S12	Troubleshooting and Problem Solving	3.8 ± 0.7
S13	Calculating and Understanding Key Metrics and Parameters	4.1 ± 0.5
S14	Equipment Maintenance	-
S15	Using and Operating Machines	3.9 ± 0.7

5.4 Observational Results

Table 5.4 presents the observed performance scores across the defined skills. The highest normalized average was found for S9 - Documentation and Monitoring of Production Data , followed by S12 - Troubleshooting and Problem Solving and S5 - Using Personal Protective Equipment (PPE).

S1 - Collaboration, Communication, and Teamwork and S4 - Following Work Instructions and Recipes also showed relatively high observed performance. In contrast, lower scores were noted for S10 - Handling Sensitive Materials, Equipment, and Products, S7 - Conducting Product Sampling, and S8 - Detecting Defective

Products.

Several skills were not observed at all and are therefore not included in the results: S2 -Curiosity and Lifelong Learning, S13 - Calculating and Understanding Key Metrics and Parameters, and S14 - Equipment Maintenance.

Table 5.4: Observational scores: raw and normalized

Skill	Skill Name	Raw Mean ± SD	Normalized Mean ± SD
S1	Collaboration, Communication, and Teamwork	0.4 ± 0.5	3.8 ± 1.1
S2	Curiosity and Lifelong Learning	-	-
S3	Applying and Following Standardized Work Methods	0.1 ± 0.6	3.1 ± 1.2
S4	Following Work Instructions and Recipes	0.1 ± 0.7	3.3 ± 1.4
S5	Using Personal Protective Equipment (PPE)	0.4 ± 0.8	3.8 ± 1.6
S6	Accuracy and Focus	0.0 ± 0.7	3.1 ± 1.4
S7	Conducting Product Sampling	-1.0 ± 0.0	1.0 ± 0.0
S8	Detecting Defective Products	-1.0 ± 0.0	1.0 ± 0.0
S9	Documentation and Monitoring of Production Data	1.0 ± 0.0	5.0 ± 0.0
S10	Handling Sensitive Materials, Equipment, and Products	-0.7 ± 0.8	1.7 ± 1.6
S11	Thinking Sequentially	-0.1 ± 0.7	2.9 ± 1.5
S12	Troubleshooting and Problem Solving	0.6 ± 0.5	4.3 ± 1.1
S13	Calculating and Understanding Key Metrics and Parameters	-	-
S14	Equipment Maintenance	-	-
S15	Using and Operating Machines	0.1 ± 0.8	3.2 ± 1.5

5.5 Triangulation of Assessment Results

The triangulation of the data entailed comparing the different methods and their alignment. This was done on both an individual level and a group level. At the individual level, the results are illustrated using radar charts, which display how individuals rated themselves compared to evaluations by trainers and observers.

Figures 5.3–5.6 present four examples, each corresponding to a different individual. These charts show how each person was assessed across a set of skills using all three methods.

It is noteworthy that Individuals C (Figure 5.5) and D (Figure 5.6) were not evaluated on the skill Handling Sensitive Materials, Equipment, and Products (S10), whereas Individuals A (Figure 5.3) and B (Figure 5.4) were assessed on this skill by all methods.

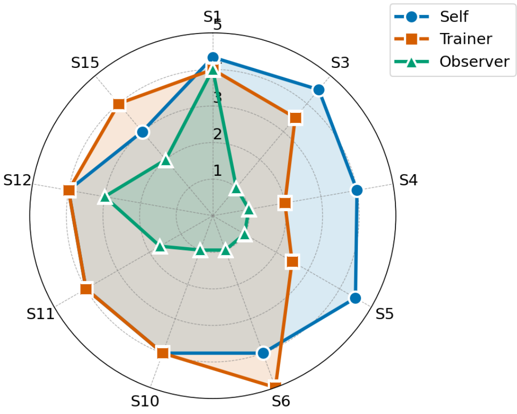

Figure 5.3: Individual A

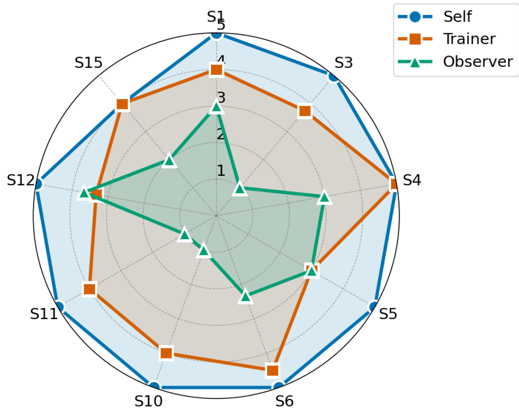

Figure 5.4: Individual B

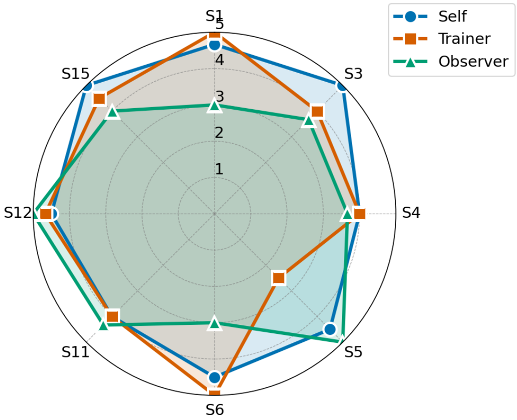

Figure 5.5: Individual C

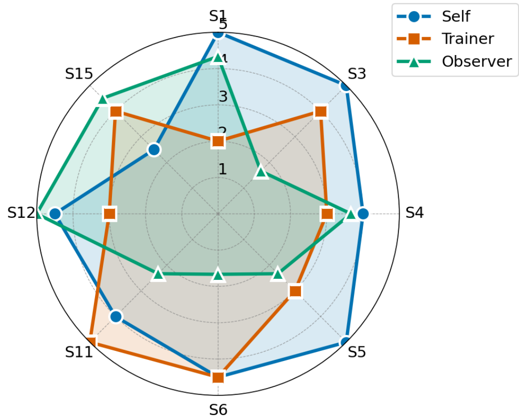

Figure 5.6: Individual D

While individual radar charts provide insight into personal differences across assessment methods, the group-level analysis offers a broader view of overall trends and potential systemic patterns in how skills are evaluated. The following tables present differences on an aggregated level. To aid interpretation, all tables comparing assessment results include row color-coding based on the magnitude of the difference between methods. Green rows indicate small differences ($|x| < 0.4$), yellow moderate differences ($0.4 \leq |x| < 1.0$), and red large differences ($|x| \geq 1.0$).

The majority of the participants scored their own skill levels higher than compared to what the trainers assessed. Table 5.5 presents a comparison between employees' initial self-ratings and the corresponding trainer assessments. The Difference column reflects the average score gap for each skill, calculated as Trainer rating minus Self-evaluation, where negative values indicate that the self-evaluation was scored higher. The Higher Self-Ratings column reports the number of participants who rated themselves higher than their trainer did, providing a count of individual instances of overestimation. The Valid Comparison Cases column indicates the number of participants who received both a trainer assessment and completed a self-evaluation for that skill, ensuring that the data reflects only directly comparable ratings. The largest difference between the two methods can be seen in S4, Applying and Following Standardized Work Methods, and S5, Using Personal Protective Equipment (PPE). For these skills the trainers has ranked the participants on average one point less than their initial self-evaluation.

Table 5.5: Self vs. Trainer Ratings by Skill

Skill	Difference	Higher Self-Ratings	Valid Comparison Cases
S1	-0.6	23	41
S2	-0.8	36	49
S3	-0.6	32	46
S4	-1.2	29	42
S5	-1.0	39	49
S6	-0.2	23	49
S7	0.1	12	43
S8	0.0	17	40
S9	0.3	5	43
S10	-0.2	18	43
S11	-0.1	15	40
S12	-0.3	27	49
S13	0.4	8	34
S14	-	-	-
S15	0.6	12	49

Table 5.6 presents a comparison between employees' initial self-ratings and the corresponding observational assessments for each skill. The Difference column reflects the average score gap (Observation minus Self-evaluation), where negative values indicate that participants rated their performance higher compared to what was observed in practice. The Higher Self-Ratings column shows the number of participants who rated themselves higher than the observed performance level. The Valid Comparison Cases column reports the number of participants for whom both a self-evaluation and an observational assessment were available. The largest gap

between self-evaluated skill level and observed was for skill S10, Handling Sensitive Materials, Equipment, and Products.

Table 5.6: Initial Self-Evaluation vs. Observations

Skill	Difference	Higher Self-Ratings	Valid Comparison Cases
S1	-0.6	26	41
S2	-	0	0
S3	-1.2	27	34
S4	-1.0	29	42
S5	-0.6	16	43
S6	-1.0	26	41
S7	-2.0	1	1
S8	-2.8	3	3
S9	1.2	0	10
S10	-2.4	16	20
S11	-1.3	24	34
S12	0.3	12	39
S13	-	0	0
S14	-	0	0
S15	-0.2	22	42

Table 5.7 compares trainer assessments with observational assessments. The Difference column shows the average score gap, calculated as Trainer rating minus Observation, where positive values indicate that trainers rated participants higher than observers did. Valid Comparison Cases column indicates the number of participants for whom both a trainer rating and an observational assessment were available.

Table 5.7: Trainer Ratings vs. Observations by Skill

Skill	Difference	Valid Comparison Cases
S1	0.2	35
S2	-	-
S3	0.6	34
S4	-0.2	40
S5	-0.5	46
S6	1.0	43
S7	3.0	1
S8	3.0	2
S9	-0.6	10
S10	2.2	22
S11	1.4	27
S12	-0.5	43
S13	-	-
S14	-	-
S15	0.7	44

5.6 Influence of Demographics

Using the demographics, the data was analyzed to see underlying patterns. In this result section, the different methods, initial self-evaluation, observations, and trainer evaluation was analyzed based on gender, educational history, work experiences, and age. The result is presented in the tables below.

Table 5.8 presents the average scores sorted by gender (F - Female, M - Male) and assessment source: self-assessment (Self), trainer evaluation (Tr), and observer rating (Ob).

Table 5.8: Mean Scores by Skill, Gender, and Source

Skill	Self–F	Self–M	Tr–F	Tr–M	Ob–F	Ob–M
S1	4.7	4.4	4.1	3.9	4.0	3.8
S2	4.7	4.4	3.8	3.7	-	-
S3	4.6	4.1	4.2	4.1	3.5	3.7
S4	4.4	4.4	3.3	3.2	2.7	3.1
S5	4.5	4.3	3.7	3.2	3.7	3.9
S6	4.3	4.3	4.3	3.9	2.9	3.2
S7	3.6	3.6	3.7	3.8	2.5	1.0
S8	4.1	4.0	4.1	4.2	5.0	1.0
S9	4.1	4.1	4.5	4.3	3.4	3.1
S10	4.1	4.1	3.9	4.0	3.2	1.3
S11	4.3	4.1	4.2	4.2	4.4	4.3
S12	4.1	4.1	3.9	3.8	2.5	2.9
S13	3.5	3.7	4.1	3.9	-	-
S14	3.4	3.5	-	-	-	-
S15	3.4	3.4	4.1	3.9	3.4	3.0

In Table 5.9, the assessments are grouped based on the highest level of education of the participants. The educational data were collected for three levels: upper secondary school (labeled as USS), university (labeled as UNI), and vocational education and training (labeled as VET). The assessment methods are abbreviated as Self for self-assessment, Tr. for trainer evaluation, and Obs. for observer rating.

Table 5.9: Evaluation Scores by Skill and Educational Background

Education	**USS**			**UNI**			**VET**		
Skill	Self	Tr.	Obs.	Self	Tr.	Obs.	Self	Tr.	Obs.
S1	4.5	3.9	3.9	4.5	4.4	3.4	4.5	3.9	4.1
S2	4.5	3.8	-	4.4	3.8	-	4.6	3.7	-
S3	4.3	3.8	3.0	4.0	3.4	3.2	4.4	3.8	3.3
S4	4.3	3.1	-	4.4	3.2	-	4.5	3.4	-
S5	4.5	3.8	1.0	3.9	4.0	-	4.1	4.0	1.0
S6	4.0	4.3	3.4	4.3	3.7	3.3	4.5	3.8	3.5
S7	3.1	3.9	2.8	3.5	3.8	-	3.8	3.7	1.0
S8	3.9	4.3	5.0	3.9	4.3	5.0	4.1	4.3	5.0
S9	4.0	4.5	3.0	3.8	4.3	2.9	4.2	4.3	3.0
S10	4.0	4.0	1.4	3.8	3.6	3.2	4.4	3.7	3.3
S11	4.0	4.3	2.8	4.1	4.3	2.8	4.4	3.8	4.5
S12	4.0	3.8	-	4.0	3.7	-	4.2	3.5	4.3
S13	3.3	4.4	-	3.6	4.0	-	4.0	3.9	-
S14	3.0	-	-	3.5	-	-	3.8	-	-
S15	2.8	4.0	3.5	3.5	3.8	3.2	3.8	3.7	1.0

A comparison between individuals with and without prior industry experience was also conducted. As shown in Table 5.10, average scores across all assessment methods—Self, Trainer, and Observer—are grouped by whether participants reported having previous experience in an industrial setting (HasExp) or not (NoExp).

Table 5.10: Average skill assessment scores reported by participants with and without prior industry experience, categorized by assessment source (Self, Trainer, Observer)

Skill	**Self**		**Trainer**		**Observer**	
	HasExp	NoExp	HasExp	NoExp	HasExp	NoExp
S1	4.6	4.4	4.1	3.7	4.0	3.5
S2	4.5	4.4	3.9	3.4	—	—
S3	4.6	3.2	3.7	3.6	3.2	3.2
S4	4.5	4.1	3.3	2.9	3.2	3.3
S5	4.6	3.8	3.5	3.0	3.7	4.1
S6	4.4	3.9	4.1	3.8	3.1	3.4
S7	3.6	2.7	3.9	3.6	—	1.0
S8	4.2	3.4	4.2	4.0	5.0	5.0
S9	4.2	3.8	4.4	4.3	3.4	3.4
S10	4.3	3.6	4.0	4.0	1.9	1.7
S11	3.6	2.7	4.0	3.8	3.3	2.3
S12	3.6	3.2	3.9	3.6	—	1.0
S13	3.7	3.5	4.1	4.0	—	—
S14	3.6	2.8	—	—	—	—
S15	4.2	3.8	3.5	3.0	3.7	4.1

The final comparison was conducted across age groups to examine potential differences in how individuals assess and are assessed based on their age. As shown in Figures 5.7-5.9. The results are grouped by age, 18–24, 25–34, 35–44, and 45–54, and each figure presents how the different age groups have been scored on average depending on assessment methods. Some skills have been labeled with a score of zero which represent that the group has not been scored in that specific area. See Appendix F for complete data.

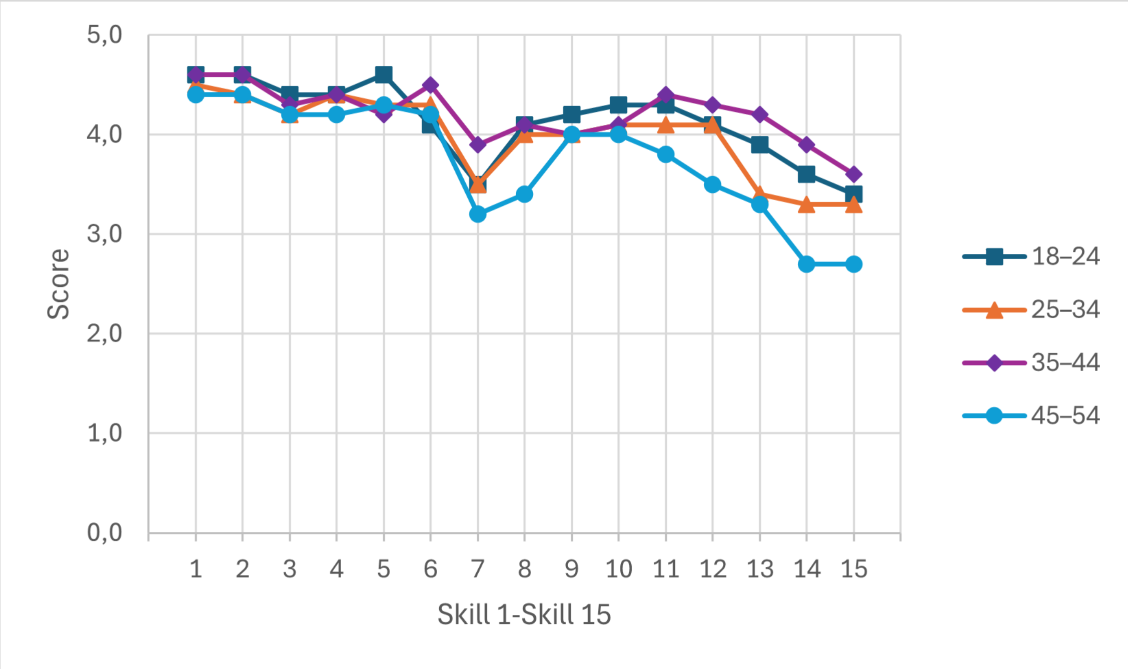

Figure 5.7: Average self-evaluation scores grouped by age

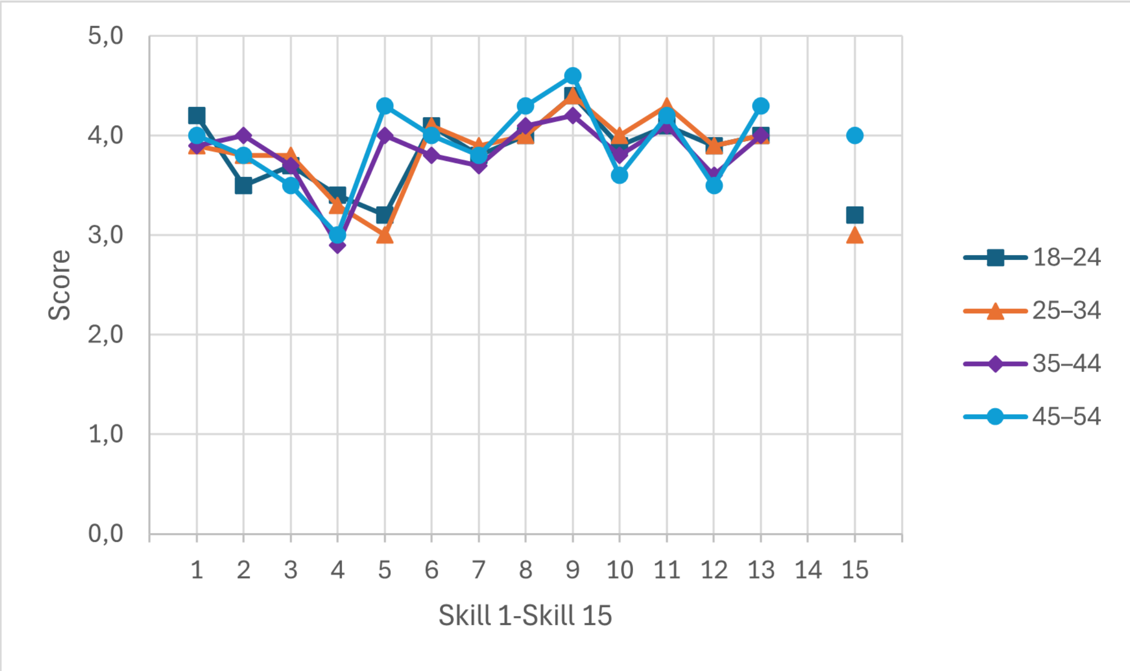

Figure 5.8: Average trainer evaluation scores grouped by age

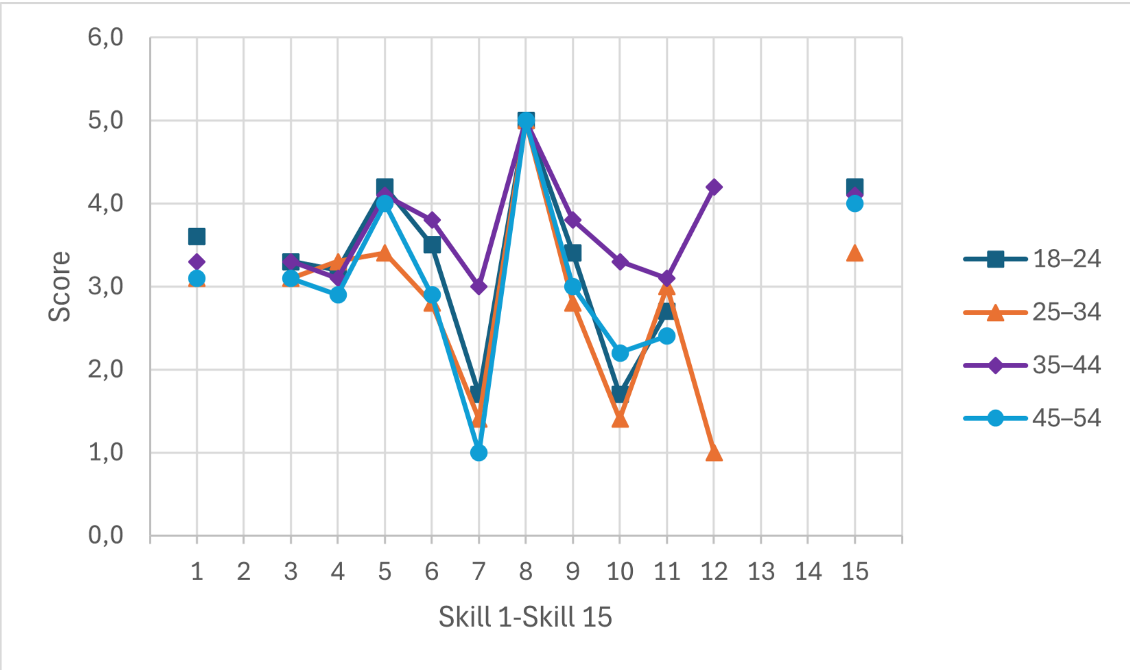

Figure 5.9: Average observation scores grouped by age

6
Discussion

This chapter aims to highlight and interpret the main findings of the study, reflect on the implications, limitations, and context-specific relevance of the different assessment methods explored.

6.1 Key Findings and Interpretation

This study revealed consistent differences between the assessment methods, particularly between self-assessment and the evaluations from trainers and observers. In most cases, participants rated their skills higher than both trainer and observer assessments, suggesting a tendency of overestimation. This pattern was especially seen in certain skill areas, such as Following Work Instructions and Recipes (S4) and Using Personal Protective Equipment (S5), where the average difference exceeded one full point on the Likert scale for the trainer assessments. When compared to the observer assessments, S4 differed by one full point, and S5 differed with 0.6. A closer look at S4 further illustrates this discrepancy. Neither trainers or observers consistently rated participants at or above 4, the level indicating a clear demonstration of the skill. Instead, most ratings hovered around 3, suggesting that participants may follow instructions inconsistently or only partially. This implies a skill level that could be considered insufficient for reliable performance.

These findings align with prior research and support insights from the literature review (see Sections 3.4 and 5.1), which indicate that self-assessments are often influenced by overconfidence or limited self-awareness—particularly among less experienced individuals.

When comparing the initial self-evaluations with those completed at the end of training, only minor changes were observed overall. However, the most notable increases occurred in skill areas where participants had initially rated themselves below four on the Likert scale. These skills included S7: Conducting Product Sampling, S13: Calculating and Understanding Key Metrics and Parameters, S14: Equipment Maintenance, and S15: Using and Operating Machines. This could indicate that participants felt more confident in these specific skills after training. Alternatively, as stated in [59] following the Dunning–Kruger effect, it may suggest that they did not gain enough insight during training to accurately recognize their own limitations, highlighting the ongoing challenge of relying on self-perception.

Additionally, the skills where participants had ranked themselves below a four on the Likert scale could be categorized as hard skills according to the definition of hard skills in [31]. As stated in [61], this may indicate that participants had higher self-efficacy in softer and more familiar skill areas.

6.2 Comparing Assessment Methods

This section explores how different assessment methods reflect varying perspectives and highlights some of their respective strengths and limitations.

6.2.1 Self-Assessments: Perceived Competence and Reflection

The difference between perceived and observed skills can be understood through the Johari Window model, which describes how parts of a person's self-awareness fall into areas that are either known or unknown to themselves and others[57]. Some participants may operate within the blind area, meaning they are unaware of certain weaknesses that are visible to trainers or observers. This could explain the overestimations found in the self-assessments. However, the model also presents the hidden area, where individuals may be aware of certain skills or knowledge that are not visible to others. This raises the possibility that the self-assessment may actually reflect something that the other methods do not see.

As discussed in the theoretical framework, psychological constructs such as the Dunning–Kruger effect and self-efficacy theory help explain why individuals may perceive their skill levels to be higher than it is in practice. Despite the limitations, self-assessments continue to be important for encouraging reflection and self-directed learning.

6.2.2 Trainer Assessments: Expert Judgement with Constraints

Trainer evaluations worked well in the BCG training environment, particularly when the trainers had sustained interaction with the participants. Their contextual expertise allowed for informed judgments on participant skill. However, these evaluations rely on consistent criteria and are resource-intensive, limiting their use in large-scale or remote settings. They may be most appropriate in practical training programs.

While offering an external viewpoint, the limitations of the trainers' evaluations are the risk of being influenced and biased based on interpersonal dynamics, familiarity with participants, or subjective interpretations of performance. There is no guarantee that a participant would receive the same score from a different trainer, as the baseline for assigning a certain score may vary between evaluators. Additionally, trainers may not be able to observe every aspect of a participant's performance. A key moment where a participant performs especially well, or struggles significantly, might be missed, resulting in a score that does not fully reflect the individual's actual skills.

[36] discusses various methods for assessing skill gaps, one of which is manager assessments. According to the categorization presented in this thesis, these assessments fall under the broader category of human observation, which aligns with the trainer assessments used in this study. The report also highlights a key limitation of such methods: the potential for bias from peers and managers. This limitation supports the concerns raised in this thesis regarding subjectivity and inconsistency in trainer evaluations. As noted, interpersonal dynamics, varying expectations, and incomplete observation of participant performance can all affect the reliability.

6.2.3 Observed Performance: Objective but Context-Limited

Compared to trainer evaluations, the observational assessments aimed to capture performance more objectively by focusing on what participants actually did during specific tasks. Observational assessments measured task-related performance. In contrast to trainer evaluations, which prior interactions or generalized impressions can influence, observational assessments were tied to specific tasks and performance indicators, such as whether the participant completed a task accurately, efficiently, or within a certain time.

In this study, the observation results revealed some discrepancies in specific skill areas. While the lowest scores were recorded in Conducting Product Sampling (S7) and Detecting Defective Products (S8), these results should be interpreted with caution. Very few participants were evaluated on these specific skills, and the scores they received were often extreme (e.g., -1), which, after normalization, resulted in a minimum value of 1. Although this could signal a gap between perceived and demonstrated skills, the limited sample size makes it difficult to draw definitive conclusions. A more reliable example can be seen in Handling Sensitive Materials, Equipment and Products (S10), where a clear gap emerged between relatively high self- and trainer scores and much lower observational results. This may indicate that participants were overconfident or insufficiently prepared for the precision or care required in that task. The score for S10 differed between the trainer and the observations as well (trainer average: 3.8 and observer average: 1.7) could indicate that the trainers missed certain tasks or critical steps while the observer saw it.

6.3 How Demographics Shape Assessment Outcomes

In addition to the general differences between assessment methods, some patterns emerged across participant demographics. Participants with prior industrial experience tended to rate themselves slightly higher across most skills and also received higher trainer evaluations in several areas. This suggests that experience may positively influence both self-perception and how the skills are judged by others from a holistic perspective. These patterns align with the concept of mastery experiences in self-efficacy theory, which suggests that individuals who have previously succeeded in a given context are more likely to develop a strong belief in their ability to perform similar tasks in the future[61]. Depending on the similarity of tasks performed in past jobs, the transferability of learning may have supported not only a stronger sense of self-efficacy but also more confident and accurate performance during the assessments[66]. Higher self-efficacy may also influence motivation and the level of effort invested in a task, which in turn could positively affect how participants are evaluated by trainers.

Gender-based patterns were also cross-referenced between the assessment methods. Female participants generally rated themselves slightly higher than male participants across most skills. Interestingly, this trend was supported by trainer evaluations, where women often received equal or slightly higher scores than men. Moreover, the gap between self-assessments and trainer ratings was often smaller for women than for men, suggesting that female participants' self-perceptions were more closely aligned with how their skills were assessed. This could indicate greater accuracy in self-evaluation among women when compared to trainer evaluations; however, the difference is small and would need further investigation. When analyzing the observer results between male and female participants, the results were mixed, and it was harder to see a consistent pattern. This outcome contrasts with findings in [63], which suggest that women tend to rate their abilities lower than men in male-dominated fields. Notably, this pattern did not emerge in the present study, suggesting that gender-related differences in self-perception may be more nuanced and context-dependent.

Differences across educational backgrounds were also explored, though no strong or consistent trends were found in the observational data. In a few skills—such as Thinking Sequentially (S11) and Troubleshooting and Problem Solving (S12), participants with vocational education and training received higher observation scores compared to those from university or upper secondary school backgrounds. This may reflect the practical orientation of vocational programs, which often emphasize applied problem-solving. However, in other areas, such as Using and Operating Machines (S15), VET participants received lower observational scores, suggesting that performance differences cannot be explained by education level alone.

Age-related differences were minimal overall. While the oldest age group, 45-54, tended to rate themselves slightly lower in some self-assessment categories, trainer and observer evaluations did not reflect any consistent pattern across age groups. Suggesting that age alone did not strongly influence either perceived or demonstrated skill levels in this study.

6.4 Choosing the Right Assessment for the Right Purpose

Assessing skills is not a neutral or uniform process—it is shaped by the perspective of the evaluator and the method used. In the experimental part of this study, three assessment approaches were employed: self-assessment, trainer evaluation, and structured observation. Each method offers a distinct view of participants' skills. While all methods aim to assess the same underlying skills, they capture different dimensions: self-assessment reflects perceived ability, trainer evaluations reflect expert judgment, and observations reflect demonstrated behavior.

Self-assessment methods proved useful in training settings that emphasize personal development, reflection, and learner engagement. This was reflected in [38], where self-assessment was seen as a viable option to guide students towards new areas of development. Their scalability and ease of implementation make them especially suitable for large groups and digital learning platforms. However, due to the subjective nature and risk of bias, self-assessments are less suited for high-stakes assessments.

Trainer evaluations provide context-specific expertise but are resource-intensive and potentially subjective. Observational assessments, focused on performance metrics, were effective in capturing task execution. However, the challenge of observer availability and limited task coverage makes them difficult to scale. In the setting at BCG, these observational assessments focusing on performance metrics could, to some extent, be automated. Automating these could reduce the need for human resources and ensure that each metric is captured with precision.

Other methods identified in the literature, such as test-based, computer-aided, or AI-supported assessments, were not applied in this study but show potential. The suitability of these methods will depend on the specific goals, resources, and scale of the assessment context.

6.4.1 Creating Upskilling and Reskilling Paths from Assessments

In [36], the most common approach to measuring skill gaps was presented to be self-evaluations. For bridging the skills gap, this would then serve as a guide for identifying which areas need improvement. When compared to the findings of this study, it suggests that if we are to tailor upskilling and reskilling initiatives based on assessments, an understanding of how different assessment methods capture various dimensions of skills is required. If used to guide training pathways, these assessments could lead to different conclusions about which skills need development.

[38] concluded that upskilling in the industrial sector is becoming essential to remain competitive. As stated in [42], the operator plays a central role in production.

Therefore, to effectively support operator upskilling, it is critical to identify specific areas in need of improvement.

For example, self-assessments might highlight areas where participants feel uncertain or lack confidence. The reason they score themselves lower might be that they recognize the importance of these skills and understand that they need to be developed. In contrast, trainer and observer assessments may identify more objective gaps in performance or critical task execution that the individual is not aware of. For example, realizing the consequences of specific mistakes or missed steps may only become visible through structured observation or external evaluation. When inspecting the radar charts on an individual level (Figures 5.3–5.6), it is clear that the different methods identify different areas for development.

To visualize how different training paths can be created depending on what method is used, the Figures 6.1-6.3 were created. These are based on individual D presented in Figure 5.6. Figure 6.1 illustrates the training path derived from self-evaluation, which includes only the skills where the participant rated themselves below four. When comparing the different paths, it is evident that the self-assessment path is the shortest, especially in contrast to the paths based on trainer evaluations (Figure 6.2) and structured performance based observations (Figure 6.3).

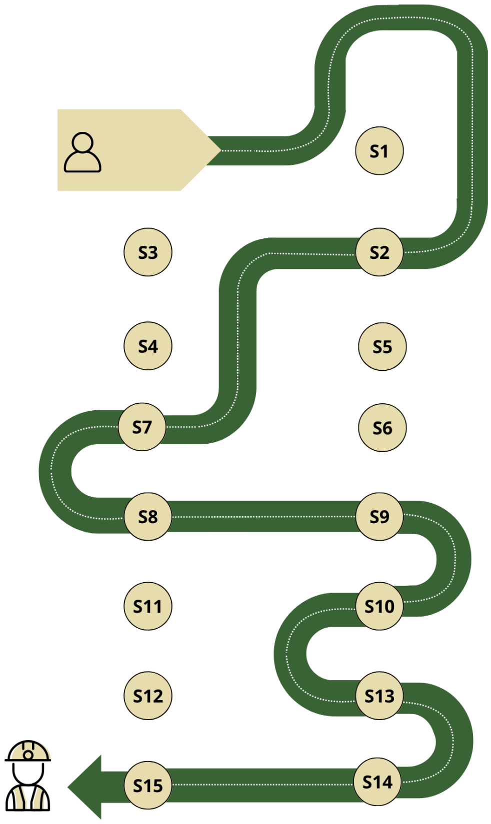

Figure 6.1: Training path for Individual D based on Self-Evaluation

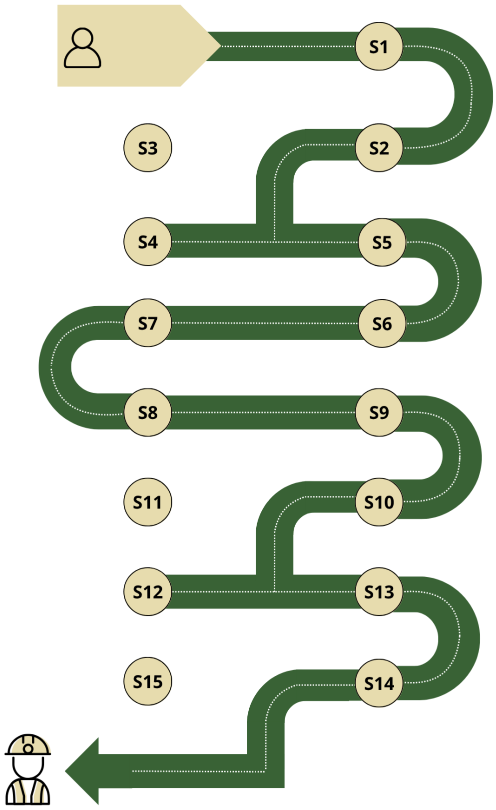

Figure 6.2: Training path for Individual D based on Trainer-Evaluation

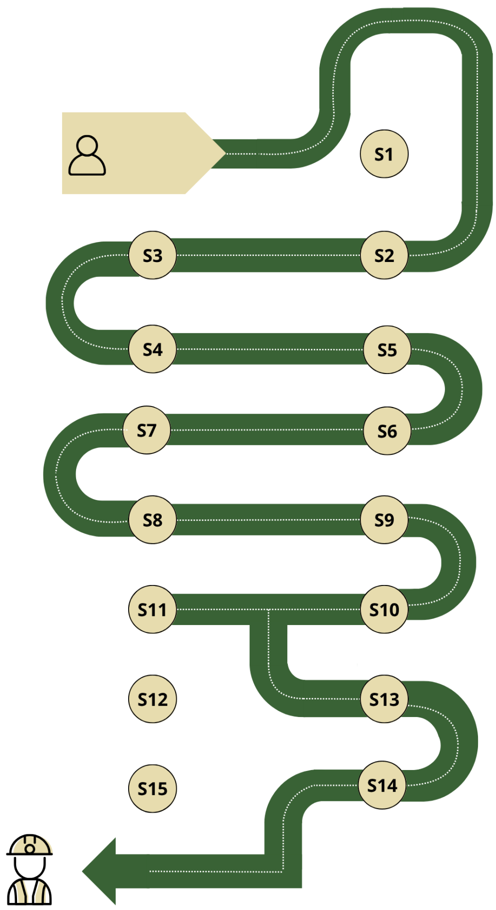

Figure 6.3: Training path for Individual D based on structured observations

6.5 Relevance Across Manufacturing Settings

Traditional approaches for addressing skill gaps across industries include training and recruitment. As noted by [30], one of the most competitive factors in manufacturing is having employees with the right skills. However, the persistent and growing skill gap within the manufacturing sector increases the pressure to accurately identify which areas require targeted training.

At the same time, recruitment is becoming increasingly challenging due to labor shortages and demographic changes [38]. This shift is prompting companies to expand their talent pools to include a broader range of applicants from diverse educational, cultural, and professional backgrounds.

In both cases, whether upskilling existing workers or onboarding individuals, the question about what skills these individuals already have arises. Using different skill assessment methods could be a key solution to identify the skills the individuals have and target development needs.

Despite this thesis focusing on specific stages of battery production, the assessment methods explored are likely applicable across various industries. These methods could be extended to other manufacturing steps beyond the training setup tested in this study. However, the effectiveness of such applications depends on clearly defining the skills to be assessed. This reflects the first step in addressing and measuring skill gaps, as outlined by [37], which emphasizes the importance of identifying the need for specific skills.

The skills used in this study was specific for battery operators but when comparing to the skills needed in the manufacturing sector in general there are some transferable skills. [42] highlight's the importance of having an operator with problem solving skills, which is also pointed out as one of the 15 skills used for this thesis. Moreover, handling automated production systems and machines is applicable in all manufacturing industries and are covered in this project under S15, Using and Operating Machines and S14, Equipment Maintenance.

6.6 Methodological Reflections

The methodological design of the experimental study combined self-assessment, trainer evaluation, and observational assessment to gain insight into how participants' skill levels were perceived and demonstrated. The aim was to explore the perspectives each method captured, and how these aligned, or differed, when applied in practice.

One important limitation relates to the use of relative and normalized scoring. Observational assessments were based on raw performance (e.g., timing or task correctness) and then converted into a +1/0/−1 scale before being normalized to a five-point Likert-like structure. This process, while practical, compressed variation, especially in cases like Conducting Product Sampling (S7) and Detecting Defective Products (S8), where few participants were assessed and all received extreme scores. As a result, the normalized values may overstate differences or suggest a level of precision not supported by the data.

In Scenario-based Industrial Training, timing data was analyzed using a five-number summary (minimum, Q1, median, Q3, maximum), and groups were categorized as fast, average, or slow, then scored accordingly. In Skill Training, task correctness was recorded using Yes/No checklists. Each task was linked to one or more skills, allowing performance to be translated into relative skill scores. Although efficient, this approach assumes that relative standing within the group accurately reflects skill levels, which may not always be true.

An alternative would have been to use absolute performance thresholds, e.g., defining what constitutes a score of 5 based on objective criteria. However, in the absence of established baselines, the relative model was considered the most practical solution for this context.

In addition, the trainer evaluations could be subjective or influenced by the fact that all trainers had their own frame of reference for what constituted strong or weak performance. This variability could have been further mitigated by developing more detailed rubrics.

Another methodological consideration relates to how skills were predefined and at what level they were described. The assessment framework in this study relied on a fixed set of 15 skill definitions, which were established based on [46, 48, 49] and used across all methods. While this structure enabled consistency and comparability, it also constrained flexibility. In some cases, it may have been difficult to determine whether a specific task outcome genuinely reflected a specific skill, or if multiple skills overlapped. Additionally, some skills were defined at a relatively broad level, for example, Using and Operating Machines, which could result in varied interpretations across trainers and participants. The forms for both trainers and participants were broken down into sub-questions related to each specific skill, but the interpretation of those sub-questions could still be different. This introduces a risk that assessments were not only influenced by performance but also by how well the assessor understood the intention behind each skill. As no discussion or interview was held with either participants or trainers, no additional information was collected about how the questions were interpreted or how each skill was understood in practice. This limits the ability to evaluate whether the assessment forms were used consistently or whether certain aspects of the skills may have been overlooked or misunderstood.

Another factor that may have influenced the assessment results is the nature of the training environment itself. The sessions were conducted in what is defined as a learning factory in [52], which emphasized experimentation, feedback, and growth rather than formal evaluation. This could have contributed to a higher sense of psychological safety, which among participants encouraged them to test and experiment as stated in [65]. While a psychologically safe environment is beneficial for learning, it may also influence how seriously they engage with evaluation tasks. Similarly, trainers may have been inclined to offer more encouraging feedback in this context, subtly affecting scoring outcomes.

6.7 Future Research

This study focused on three methods, but future research could explore the integration of other techniques, such as test-based, computer-aided, or AI-supported assessments. These approaches may offer new insights, particularly around theoretical knowledge, real-time task monitoring, or scalable feedback in large-scale settings.

The experimental study focused on the setting at BCG and the skills applicable to this setting. However, continuing to explore how the skills identified and trained at the initiatives described in other European projects, such as InnoEnergy Skills Institute, [55], and the EBA, [53], could offer additional depth. The battery industry was the main focus, but some skills are transferable to other industries. Recognizing that the manufacturing sector has the largest amount of skill gaps described in [37], shows the need for a broader study on how to capture skills on an individual level.

The training set-up is assumed to match the steps in battery production as described in [25], aligning with the Li-ion production process. The transferability of the skills has not been evaluated in this thesis, as it was assumed that BCG has taken this into account. However, exploring learning transferability, as described in [66], could provide valuable insight into how well assessments in this learning factory setting represent actual performance in real production environments.

Further investigation is also needed into how assessment outcomes are influenced by participant background factors, such as experience, gender, or education. While this study provided some exploratory insights, a larger and more diverse sample would be needed to draw stronger conclusions. Additionally, examine how these groups perform across different categories of skills, such as those described in [31, 32].

Another area for development is establishing performance benchmarks. The relative scoring approach used here worked within the constraints of the study but highlights the value of having clearer standards for interpreting skills. Future studies could explore how to define these thresholds in industrial training, and how different evaluators apply them.

Lastly, qualitative follow-ups, such as interviews with participants and trainers, could offer deeper insight into how assessment tools are understood and experienced. This could strengthen the design and interpretation of future skill assessments across various industrial domains.

7
Conclusion

This study aimed to explore how skills can be effectively assessed for operators in the battery industry through a combination of literature review and empirical data collection in a practical training setting. It focused on one main question: How can operator skills be assessed effectively? By addressing two sub-questions: how different assessment methods reflect various perspectives, and in which contexts specific methods are most suitable.

Seven categories of skill assessment methods were identified: self-assessment, test-based, human observation, performance-based, computer-aided, AI-supported, and background-based. Each method has strengths and limitations; for example, test-based methods offer scalability but are limited in assessing practical skills, while observational approaches better capture hands-on skills but are resource-intensive.

The experimental study collected empirical data focused on three methods: self-assessment, trainer evaluation similar to human observation, and observational assessment focusing on performance metrics. Self-assessments encouraged reflection but often overestimated skill levels. Trainer evaluations offered holistic insights but were prone to subjectivity. Assessments focusing on performance metrics captured real-time task execution but were constrained by the challenges of having and collecting information through a protocol.

Each method reflected different dimensions of skill: self-assessment showed perceived ability influenced by psychological factors; trainer evaluation reflected expert judgment; and observational methods provided objective performance data within practical constraints.

The choice of method should align with the purpose and context of the assessment. Self-assessments are suitable for scalable, early-stage mapping; trainer evaluations fit small-group, hands-on training; and performance-based methods are ideal for task evaluation, though they require technological support for broader application. Emerging technologies, such as AI and video analysis, present promising opportunities to enhance objectivity, feedback quality, and scalability in future skill assessments.

Bibliography

[1] A. Sharma and B. J. Singh, "Evolution of industrial revolutions: A review," *International Journal of Innovative Technology and Exploring Engineering*, vol. 9, pp. 66–73, Sep. 2020. DOI: 10.35940/ijitee.I7144.0991120.

[2] A. Pandey and R. Sharma, "The development of manufacturing industry revolutions from 1.0 to 5.0," *Journal of Informatics Education and Research*, vol. 4, no. 1, 2024. DOI: 10.52783/jier.v4i1.710.

[3] Göteborgs Tekniska College, *Center för utbildning och kunskap om batteri • kompetens inom batteriteknik – gtc*, Accessed: January 31, 2025, Jan. 2025. [Online]. Available: https://www.goteborgstekniskacollege.se/partner/projekt-och-utveckling/battery-centre-gothenburg.

[4] United Nations, *The Paris Agreement | United Nations*, Retrieved January 29, 2025. [Online]. Available: https://www.un.org/en/climatechange/paris-agreement.

[5] European Environment Agency, "Sustainability of Europe's mobility systems," European Environment Agency, Tech. Rep. 01/2024, 2024, EN HTML: TH-01-24-007-EN-Q. DOI: 10.2800/8560026.

[6] United Nations, *COP26: Together for our planet | United Nations*, Retrieved January 29, 2025. [Online]. Available: https://www.un.org/en/climatechange/cop26.

[7] Ecorys, "The Future of the EU Automotive Sector," European Parliament, Policy Department for Economic, Scientific and Quality of Life Policies, Luxembourg, Tech. Rep., 2021, Publication for the Committee on Industry, Research and Energy.

[8] World Economic Forum, "A Vision for a Sustainable Battery Value Chain in 2030," World Economic Forum, Tech. Rep., 2019. [Online]. Available: https://www3.weforum.org/docs/WEF_A_Vision_for_a_Sustainable_Battery_Value_Chain_in_2030_Report.pdf.

[9] Maroš Šefčovič, *Press Conference Following the 5th High-Level Meeting of the European Battery Alliance*, Press Conference.

[10] Energy Battery Alliance - EBA250, *ABOUT EBA250 - European Battery Alliance*, Accessed: January 29, 2025, Dec. 2022. [Online]. Available: https://www.eba250.com/about-eba250/.

[11] European Commission, *The European Pillar of Social Rights in 20 Principles*, Accessed: January 29, 2025, Mar. 2024. [Online]. Available: https://employment-social-affairs.ec.europa.eu/european-pillar-social-rights-20-principles_en.

[12] A. Dutta, S. Mitra, M. Basak, and T. Banerjee, "A comprehensive review on batteries and supercapacitors: Development and challenges since their inception," *Energy Storage*, vol. 5, no. 1, 2022. DOI: 10.1002/est2.339.

[13] G. Pistoia, "Chapter 1 - areas of battery applications," in *Battery Operated Devices and Systems*, G. Pistoia, Ed., Amsterdam: Elsevier, 2009, pp. 1–15, ISBN: 978-0-444-53214-5. DOI: https://doi.org/10.1016/B978-0-444-53214-5.00001-7. [Online]. Available: https://www.sciencedirect.com/science/article/pii/B9780444532145000017.

[14] International Energy Agency, *Net zero by 2050*, https://www.iea.org/reports/net-zero-by-2050, IEA, Paris. Licence: CC BY 4.0, 2021.

[15] International Energy Agency, *The battery industry has entered a new phase*, https://www.iea.org/commentaries/the-battery-industry-has-entered-a-new-phase, IEA, Paris. Licence: CC BY 4.0, 2025.

[16] Energy Battery Alliance - EBA250, *Value chain - european battery alliance*, https://www.eba250.com/about-eba250/value-chain/, European Battery Alliance, Mar. 2019.

[17] Y. S. Choudhary, L. Jothi, and G. Nageswaran, "Electrochemical characterization," in *Elsevier eBooks*, Elsevier, 2017, pp. 19–54. DOI: 10.1016/b978-0-323-46140-5.00002-9.

[18] G. Marin-Garcia, G. Vazquez-Guzman, J. Sosa, A. R. Lopez, P. Martinez-Rodriguez, and D. Langarica, "Battery types and electrical models: A review," in *2020 IEEE International Autumn Meeting on Power, Electronics and Computing (ROPEC)*, vol. 4, 2020, pp. 1–6.

[19] C. Lamiel, I. Hussain, X. Ma, and K. Zhang, "Properties, functions, and challenges: Current collectors," *Materials Today Chemistry*, vol. 26, p. 101 152, 2022, ISSN: 2468-5194. DOI: 10.1016/j.mtchem.2022.101152. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2468519422003810.

[20] E. B. Tetteh, "Understanding battery types, components and the role of battery material testing in development and manufacture," *Applied Sciences From Technology Networks*, May 2024, Accessed: April 21, 2025. [Online]. Available: https://www.technologynetworks.com/applied-sciences/articles/understanding-battery-types-components-and-the-role-of-battery-material-testing-in-development-and-376993.

[21] J. Patrício, Y. Kalmykova, P. E. O. Berg, L. Rosado, and H. Åberg, "Primary and secondary battery consumption trends in sweden 1996–2013: Method development and detailed accounting by battery type," *Waste Management*, vol. 39, pp. 236–245, 2015. DOI: 10.1016/j.wasman.2015.02.008.

[22] R. Schröder, M. Aydemir, and G. Seliger, "Comparatively assessing different shapes of lithium-ion battery cells," *Procedia Manufacturing*, vol. 8, pp. 104–111, 2017, 14th Global Conference on Sustainable Manufacturing, GCSM 3-5 October 2016, Stellenbosch, South Africa, ISSN: 2351-9789. DOI: 10.1016/j.promfg.2017.02.013. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2351978917300173.

[23] Y. Mekonnen, A. Sundararajan, and A. I. Sarwat, "A review of cathode and anode materials for lithium-ion batteries," in *SoutheastCon 2016*, 2016, pp. 1–6. DOI: 10.1109/SECON.2016.7506639.

[24] A. K. Koech, G. Mwandila, F. Mulolani, and P. Mwaanga, "Lithium-ion battery fundamentals and exploration of cathode materials: A review," *South African Journal of Chemical Engineering*, vol. 50, pp. 321–339, 2024, ISSN: 1026-9185. DOI: 10.1016/j.sajce.2024.09.008. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1026918524001100.

[25] HBOWA New Energy, *From raw materials to finished product: The lithium batteries manufacturing process*, HBOWA New Energy, Jan. 2025. [Online]. Available: https://www.pretapower.com/from-raw-materials-to-finished-product-the-lithium-batteries-manufacturing-process/.

[26] T. Igogo, D. Sandor, A. Mayyas, and J. Engel-Cox, "Supply chain of raw materials used in the manufacturing of light-duty vehicle lithium-ion batteries," National Renewable Energy Laboratory (NREL), Tech. Rep., 2019. DOI: 10.2172/1560124.

[27] H. Heimes *et al.*, *Lithium-ion battery cell production process*, Accessed: April 28, 2025, 2018. [Online]. Available: https://www.pem.rwth-aachen.de/global/show_document.asp?id=aaaaaaaaabdqbtk.

[28] A. Örüm Aydin, F. Zajonz, T. Günther, K. B. Dermenci, M. Berecibar, and L. Urrutia, "Lithium-ion battery manufacturing: Industrial view on processing challenges, possible solutions and recent advances," *Batteries*, vol. 9, no. 11, 2023, ISSN: 2313-0105. DOI: 10.3390/batteries9110555. [Online]. Available: https://www.mdpi.com/2313-0105/9/11/555.

[29] Cedefop, *Terminology of European Education and Training Policy: A Selection of 130 Key Terms*, Second Edition. Luxembourg: Cedefop – European Centre for the Development of Vocational Training, 2014, Accessed: April 28, 2025. [Online]. Available: https://www.cedefop.europa.eu/files/4117_en.pdf.

[30] G. Chryssolouris, D. Mavrikios, and D. Mourtzis, "Manufacturing systems: Skills & competencies for the future," *Procedia CIRP*, vol. 7, pp. 17–24, 2013, Forty Sixth CIRP Conference on Manufacturing Systems 2013, ISSN: 2212-8271. DOI: 10.1016/j.procir.2013.05.004. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2212827113002114.

[31] A. F. Hendarman and U. Cantner, "Soft skills, hard skills, and individual innovativeness," *Eurasian Business Review*, vol. 8, no. 2, pp. 139–169, 2018. DOI: 10.1007/s40821-017-0076-6.

[32] J. Lamri and T. Lubart, "Reconciling hard skills and soft skills in a common framework: The generic skills component approach," *Journal of Intelligence*, vol. 11, no. 6, p. 107, 2023. DOI: 10.3390/jintelligence11060107.

[33] A. S. George and A. H. George, "Industrial revolution 5.0: The transformation of the modern manufacturing process to enable man and machine to work hand in hand," *Journal of Seybold Report ISSN NO*, vol. 1533, no. 9211, pp. 1525–68 128, 2020.

[34] D. Romero *et al.*, *The 2024 World Manufacturing Report: New Perspectives for the Future of Manufacturing: Outlook 2030*, English. World Manufacturing Foundation, Oct. 2024.

[35] A. Mital *et al.*, "The need for worker training in advanced manufacturing technology (amt) environments: A white paper," *International Journal of Industrial Ergonomics*, vol. 24, no. 2, pp. 173–184, 1999, ISSN: 0169-8141. DOI: https://doi.org/10.1016/S0169-8141(98)00024-9. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0169814198000249.

[36] P. Rikala, G. Braun, M. Järvinen, J. Stahre, and R. Hämäläinen, "Understanding and measuring skill gaps in industry 4.0 — a review," *Technological Forecasting and Social Change*, vol. 201, p. 123 206, 2024, ISSN: 0040-1625. DOI: https://doi.org/10.1016/j.techfore.2024.123206. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0040162524000027.

[37] OECD, *Understanding Skill Gaps in Firms: Results of the PIAAC Employer Module* (OECD Skills Studies). Paris: OECD Publishing, 2024. DOI: 10.1787/b388d1da-en.

[38] G. Braun, P. Rikala, M. Järvinen, R. Hämäläinen, and J. Stahre, "Bridging skill gaps – a systematic literature review of strategies for industry," in *Sustainable Production through Advanced Manufacturing, Intelligent Automation and Work Integrated Learning*, ser. Advances in Transdisciplinary Engineering, vol. 52, 2024, pp. 687–696. DOI: 10.3233/ATDE240209. [Online]. Available: http://dx.doi.org/10.3233/ATDE240209.

[39] OECD, "Promoting green and digital innovation: The role of upskilling and reskilling in higher education," OECD Publishing, Paris, 2024. [Online]. Available: https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/07/promoting-green-and-digital-innovation_986b39b4/feb029df-en.pdf.

[40] OECD, "Reskilling 4 employment," OECD Publishing, Paris, 2024. [Online]. Available: https://www.oecd.org/en/publications/providing-local-actors-with-case-studies-evidence-and-solutions-places_eb108047-en/reskilling-4-employment_8edec592-en.html.

[41] The Manufacturing Institute, "Digital skills in the manufacturing sector," The Manufacturing Institute, Tech. Rep., 2024, Accessed: 2025-05-18. [Online]. Available: https://themanufacturinginstitute.org/wp-content/uploads/2024/04/Digital_Skills_Report_April_2024.pdf.

[42] D. Romero and J. Stahre, "Towards the resilient operator 5.0: The future of work in smart resilient manufacturing systems," *Procedia cirp*, vol. 104, pp. 1089–1094, 2021.

[43] Cedefop, "Machine and plant operators: Skills opportunities and challenges," Cedefop – European Centre for the Development of Vocational Training, 2023, Skills intelligence data insight.

[44] The Manufacturing Institute, Rockwell Automation, and PTC, "Building a manufacturing workforce for the future," The Manufacturing Institute, Tech. Rep., 2022, Available at: https://www.themanufacturinginstitute.org/wp-content/uploads/2022/10/NAM_Rockwell-PTC-Study.pdf. Accessed: 2025-05-18.

[45] Center for Automotive Research (CAR), "Battery industry education and training needs assessment (bietna)," Center for Automotive Research, Tech. Rep., 2024, Accessed: 2025-05-18. [Online]. Available: https://www.cargroup.org/wp-content/uploads/2024/02/CAR_BIETNA_2024_PreblicationCopy.pdf.

[46] K. Isaksson and T. Saad, "Skills mapping and training facilitation in battery cell production," Accessed: 2025-05-18, Master's Thesis, Chalmers University of Technology, 2024. [Online]. Available: http://hdl.handle.net/20.500.12380/307758.

[47] ALBATTS Project, *Albatts skills cards*, https://www.project-albatts.eu/en/skillscards, Accessed: 2025-05-18, 2024.

[48] ALBATTS Project, *Skill card 21: Production operator in battery cell manufacturing*, https://www.project-albatts.eu/Media/SkillCard/21/SkillCard_21_SKILLCARD_20230623_7420.pdf, Accessed: 2025-05-18, 2023.

[49] ALBATTS Project, *Skill card 22: Machine operator in upstream battery manufacturing*, https://www.project-albatts.eu/Media/SkillCard/22/SkillCard_22_SKILLCARD_20230623_74218.pdf, Accessed: 2025-05-18, 2023.

[50] J. M. Barron, M. C. Berger, and D. A. Black, *On-the-Job Training*. W.E. Upjohn Institute for Employment Research, 1997. DOI: 10.17848/9780585262369.

[51] B. Knoke and K.-D. Thoben, "Training simulators for manufacturing processes: Literature review and systematisation of applicability factors," *Computer Applications in Engineering Education*, vol. 29, no. 5, pp. 1191–1207, 2021. DOI: https://doi.org/10.1002/cae.22378. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/cae.22378. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1002/cae.22378.

[52] E. Abele *et al.*, "Learning factories for research, education, and training," *Procedia CIRP*, vol. 32, pp. 1–6, 2015, 5th Conference on Learning Factories, ISSN: 2212-8271. DOI: https://doi.org/10.1016/j.procir.2015.02.187. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S221282711500503X.

[53] European Commission, *European battery alliance*, https://single-market-economy.ec.europa.eu/industry/industrial-alliances/european-battery-alliance_en, Accessed: 2025-05-20, n.d.

[54] Energy Battery Alliance - EBA250, *About eba250 - european battery alliance*, https://www.eba250.com/about-eba250/, Accessed: 2025-05-20, 2025.

[55] InnoEnergy, *Innoenergy skills institute*, Accessed: 2025-05-20, n.d. [Online]. Available: https://innoenergy.com/skillsinstitute/.

[56] European Commission, Employment, Social Affairs and Inclusion, *A new european battery academy launched to boost skills for fast-growing battery ecosystem in europe*, https://employment-social-affairs.ec.europa.eu/news/new-european-battery-academy-launched-boost-skills-fast-growing-battery-ecosystem-europe-2022-02-23_en, Accessed: 2025-05-20, 2022.

[57] J. Luft and H. Ingham, "The johari window," *Human relations training news*, vol. 5, no. 1, pp. 6–7, 1961.

[58] R. Kapur, *Understanding the relevance of johari window*, https://www.researchgate.net/publication/376958357_Understanding_the_Relevance_of_Johari_Window, Accessed: 2025-05-15, 2023.

[59] J. Kruger and D. Dunning, "Unskilled and unaware of it: How difficulties in recognizing one's own incompetence lead to inflated self-assessments," *Journal of Personality and Social Psychology*, vol. 77, pp. 1121–34, Jan. 2000. DOI: 10.1037//0022-3514.77.6.1121.

[60] R. A. Jansen, A. N. Rafferty, and T. L. Griffiths, "A rational model of the dunning–kruger effect supports insensitivity to evidence in low performers," *Nature Human Behaviour*, vol. 5, no. 6, pp. 756–763, 2021. DOI: 10.1038/s41562-021-01057-0.

[61] A. Bandura, "Self-efficacy: Toward a unifying theory of behavioral change.," *Psychological review*, vol. 84, no. 2, p. 191, 1977.

[62] C. Huang, "Gender differences in academic self-efficacy: A meta-analysis," *European Journal of Psychology of Education*, vol. 28, pp. 1–35, 2013. DOI: 10.1007/s10212-012-0126-3.

[63] S. J. Correll, "Gender and the career choice process: The role of biased self-assessments," *American Journal of Sociology*, vol. 106, no. 6, pp. 1691–1730, 2001. DOI: 10.1086/321299.

[64] J. Ehrlinger and D. Dunning, "How chronic self-views influence (and potentially mislead) estimates of performance," *Journal of Personality and Social Psychology*, vol. 84, no. 1, pp. 5–17, 2003. DOI: 10.1037/0022-3514.84.1.5.

[65] A. Edmondson, "Psychological safety and learning behavior in work teams," *Administrative Science Quarterly*, vol. 44, no. 2, pp. 350–383, 1999. DOI: 10.2307/2666999.

[66] L. A. Burke and H. M. Hutchins, "Training transfer: An integrative literature review," *Human Resource Development Review*, vol. 6, no. 3, pp. 263–296, 2007. DOI: 10.1177/1534484307303035.

[67] V. Garousi, M. Felderer, and M. V. Mäntylä, "Guidelines for including grey literature and conducting multivocal literature reviews in software engineering," *Information and Software Technology*, vol. 106, pp. 101–121, 2019, ISSN: 0950-5849. DOI: https://doi.org/10.1016/j.infsof.2018.09.006. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0950584918301939.

[68] R. W. Schlosser, O. Wendt, S. Bhavnani, and B. Nail-Chiwetalu, "Use of information-seeking strategies for developing systematic reviews and engaging in evidence-based practice: The application of traditional and comprehensive pearl growing. a review," *International Journal of Language and Communication Disorders*, vol. 41, no. 5, pp. 567–582, Sep. 2006. DOI: 10.1080/13682820600742190.

[69] Ž. Martinaitis, "Measuring skills in europe," *European Journal of Training and Development*, vol. 38, no. 3, pp. 198–210, 2014. DOI: 10.1108/EJTD-05-2013-0054. [Online]. Available: https://www.emerald.com/insight/content/doi/10.1108/ejtd-05-2013-0054/full/html.

[70] R. Laajaj and K. Macours, "Measuring skills in developing countries," World Bank, Washington, DC, Policy Research Working Paper 8000, Mar. 2017. [On-

line]. Available: https://openknowledge.worldbank.org/server/api/core/bitstreams/f06e9351-9979-59fe-951b-c7548258122a/content.

[71] J. Paeßens, B. Ma, and E. Winther, "Effectiveness of collaboration in vet: Measuring skills for solving complex vocational problems with a multidimensional authentic technology-based assessment," *International Journal for Research in Vocational Education and Training*, vol. 10, no. 1, pp. 46–67, 2023. DOI: 10.13152/IJRVET.10.1.3. [Online]. Available: https://journals.sub.uni-hamburg.de/hup2/ijrvet/article/view/1012.

[72] P. Wedemeyer, "Managing skills and knowledge using online tools," *Journal of Workplace Learning*, vol. 21, no. 2, pp. 125–138, 2009. DOI: 10.1108/13665620910943960. [Online]. Available: https://www.emerald.com/insight/content/doi/10.1108/13665620910943960/full/html.

[73] A. Groen, P. Bijsmans, and J. Adriaensen, "Improving a self-assessment tool to monitor generic skills development in an active learning environment," *European Political Science*, vol. 19, no. 3, pp. 352–366, 2020. DOI: 10.1057/s41304-020-00258-x. [Online]. Available: https://link.springer.com/article/10.1057/s41304-020-00258-x.

[74] J. Allen and R. van der Velden, "The role of self-assessment in measuring skills," Research Centre for Education and the Labour Market (ROA), Maastricht, Netherlands, REFLEX Working Paper Series 2, 2005. [Online]. Available: https://www.researchgate.net/publication/228654616_The_role_of_self-assessment_in_measuring_skills.

[75] T. Kautz, J. J. Heckman, R. Diris, B. ter Weel, and L. Borghans, "Fostering and measuring skills: Improving cognitive and non-cognitive skills to promote lifetime success," OECD Publishing, Paris, OECD Education Working Papers 110, 2014. DOI: 10.1787/5jxsr7vr78f7-en. [Online]. Available: https://www.oecd.org/en/publications/fostering-and-measuring-skills_5jxsr7vr78f7-en.html.

[76] R. Pedrett, P. Mascagni, G. Beldi, N. Padoy, and J. L. Lavanchy, "Technical skill assessment in minimally invasive surgery using artificial intelligence: A systematic review," *Surgical Endoscopy*, vol. 37, no. 10, pp. 7412–7424, 2023. DOI: 10.1007/s00464-023-10335-z. [Online]. Available: https://link.springer.com/article/10.1007/s00464-023-10335-z.

[77] S. Nema and L. Vachhani, "Surgical instrument detection and tracking technologies: Automating dataset labeling for surgical skill assessment," *Frontiers in Robotics and AI*, vol. 9, p. 1 030 846, 2022. DOI: 10.3389/frobt.2022.1030846. [Online]. Available: https://www.frontiersin.org/articles/10.3389/frobt.2022.1030846/full.

[78] M. Uemura *et al.*, "Procedural surgical skill assessment in laparoscopic training environments," *International Journal of Computer Assisted Radiology and Surgery*, vol. 11, no. 4, pp. 543–552, 2016. DOI: 10.1007/s11548-015-1274-2. [Online]. Available: https://link.springer.com/article/10.1007/s11548-015-1274-2.

[79] A. Vergis and K. Hardy, "Cognitive and technical skill assessment in surgical education: A changing horizon," *Indian Journal of Surgery*, vol. 79, no. 2,

pp. 153–157, 2017. DOI: 10.1007/s12262-017-1603-5. [Online]. Available: https://link.springer.com/article/10.1007/s12262-017-1603-5.

[80] M. Ahmad, H. M. Qasim, and Q. Khushi, "Specifying criteria for the assessment of speaking skill: A library based review," *International Journal of Educational Sciences*, vol. 24, no. 1-3, pp. 23–33, 2019. DOI: 10.31901/24566322.2019/24.1-3.1075. [Online]. Available: https://krepublishers.com/02-Journals/IJES/IJES-24-0-000-19-Web/IJES-24-1-3-000-19-Abst-PDF/IJES-24-1-3-023-19-1075-Ahmad-M/IJES-24-1-3-023-19-1075-Ahmad-M-Tx%5B4%5D.pdf.

[81] J. D. Beard, P. A. Cook, D. J. Earnshaw, J. R. F. Monson, and M. G. Wyatt, "Observational tools for assessment of procedural skills: A systematic review," *The American Journal of Surgery*, vol. 201, no. 1, pp. 107–113, 2011. DOI: 10.1016/j.amjsurg.2010.08.015. [Online]. Available: https://www.americanjournalofsurgery.com/article/S0002-9610(11)00206-6/fulltext.

[82] F. Bellotti, B. Kapralos, K. Lee, P. Moreno-Ger, and R. Berta, "Assessment in and of serious games: An overview," *Advances in Human-Computer Interaction*, vol. 2013, pp. 1–11, 2013. DOI: 10.1155/2013/136864. [Online]. Available: https://onlinelibrary.wiley.com/doi/10.1155/2013/136864.

[83] H.-J. Kwon, M.-J. Kim, H.-J. Lee, E.-J. Park, and J.-W. Kim, "Technical skill training and assessment in dental education," *Journal of Dental Sciences*, vol. 16, no. 1, pp. 1–9, 2021. DOI: 10.1016/j.jds.2020.06.004. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S188276162100020X.

[84] F. Al-Shahrestani, M. S. Sørensen, and S. A. W. Andersen, "Performance metrics in mastoidectomy training: A systematic review," *European Archives of Oto-Rhino-Laryngology*, vol. 276, no. 3, pp. 657–664, 2019. DOI: 10.1007/s00405-018-05265-9. [Online]. Available: https://link.springer.com/article/10.1007/s00405-018-05265-9.

[85] M. Albaladejo-González and J. A. Ruipérez-Valiente, "Artificial intelligence to support the training and assessment of professionals: A systematic literature review," *ACM Computing Surveys*, vol. 57, no. 3, 2025. DOI: 10.1145/3699712. [Online]. Available: https://dl.acm.org/doi/10.1145/3699712.

[86] T. Industry, "How to verify and measure skills development: The value of continuous learning," *Training Industry*, 2024. [Online]. Available: https://trainingindustry.com/articles/measurement-and-analytics/how-to-verify-and-measure-skills-development-the-value-of-continuous-learning/.

[87] American Institutes for Research, "Measuring skills at work," American Institutes for Research, Tech. Rep., 2021, Accessed: 2025-05-11. [Online]. Available: https://www.air.org/sites/default/files/2021-07/AIR-Skill-Validation-2021-7-9.pdf.

[88] "Statistical approaches to the measurement of skills: 2016 edition," Eurostat, Luxembourg, Statistical Working Paper KS-TC-16-023-EN-N, 2016. DOI: 10.2785/652037. [Online]. Available: https://ec.europa.eu/eurostat/

documents/3888793/7753369/KS-TC-16-023-EN-N.pdf/438b69b5-2fcb-4923-b9e2-fa7b59906438.

[89] National Careers Service, *Discover your skills and careers*, Accessed: 2025-05-11, 2025. [Online]. Available: https://nationalcareers.service.gov.uk/discover-your-skills-and-careers.

[90] European Commission, *Europass digital skills self-assessment tool*, Accessed: 2025-05-11, 2022. [Online]. Available: https://europa.eu/europass/digitalskills/screen/home.

[91] VETASSESS, *Skills assessment for trade occupations*, Accessed: 2025-05-11, 2025. [Online]. Available: https://www.vetassess.com.au/skills-assessment-for-migration/skills-assessment-for-trade-occupations.

[92] R. Likert, "A technique for the measurement of attitudes," *Archives of Psychology*, vol. 22, no. 140, pp. 1–55, 1932.

[93] H. N. Boone and D. A. Boone, "Analyzing likert data," *Journal of Extension*, vol. 50, no. 2, pp. 1–5, 2012. [Online]. Available: https://tigerprints.clemson.edu/joe/vol50/iss2/2.

[94] L. E. F. McKechnie and A. J. Reiss, "Structured observation," in *The SAGE Encyclopedia of Qualitative Research Methods*, L. M. Given, Ed., Accessed May 8, 2025, SAGE Publications, 2008. DOI: 10.4135/9781412963909.n436.

[95] T. Davenport and L. Prusak, *Working Knowledge: How Organizations Manage What They Know.* Jan. 1998, vol. 1. DOI: 10.1145/348772.348775.

[96] V. Braun and V. Clarke, "Using thematic analysis in psychology," *Qualitative Research in Psychology*, vol. 3, no. 2, pp. 77–101, 2006. DOI: 10.1191/1478088706qp063oa.

[97] N. Bakkalbasi, D. Jaggars, and B. Rockenbach, "Re-skilling for the digital humanities: Measuring skills, engagement, and learning," *Library Management*, vol. 36, no. 3, pp. 208–214, 2015. DOI: 10.1108/LM-09-2014-0109. [Online]. Available: https://www.emerald.com/insight/content/doi/10.1108/lm-09-2014-0109/full/html.

A

Appendix: Quality Assurance Checklist

The following checklist was used to evaluate the quality of selected sources. It accommodates academic, informal, and commercial sources recommending skill assessment methods or tools.

Authority and Source Credibility:
- Is the source published by a recognized academic, governmental, or industry institution?
- Does the author or organization have relevant domain expertise or experience?
- Is the source peer-reviewed, official, or widely cited?

Clarity and Method Description:
- Is the assessment method or approach clearly and explicitly described?
- Are its use cases, context of application, or intended users explained?
- Are assumptions or limitations acknowledged?

Evidence Base and Validation:
- Is the method supported by empirical data, case studies, or trials?
- Is there external validation (e.g., evaluations, certifications, expert reviews)?
- Are concerns like generalizability, scalability, or transferability addressed?

Practical Use and Implementation:
- Has the method been applied in real-world settings (e.g., industry, training, education)?
- Does the source offer implementation details, such as tools, steps, or examples?
- Are any barriers to use discussed (e.g., technical, cost, time)?

Bias and Commercial Interest:
- Does the source promote a specific product, tool, or service?
- Are potential conflicts of interest or commercial motives disclosed?
- Is there transparency regarding performance claims or limitations?

B

Appendix: Questionnaire

Master Thesis: Self-Assessment for Skill Mapping Part 1

This questionnaire aims to map and evaluate various professional skills within the workplace, focusing on competencies that are important in the battery industry. We seek to understand how individuals perceive their own skills and how different tools for skill assessment perform. The collected data will be used to analyze how we can develop better methods for mapping skill needs in the future. The goal is to identify which skills you, as an individual, may need to reskill or upskill to work effectively in your professional role.

* Obligatoriskt

Participant Information for the Master Thesis

By completing this questionnaire, you are participating in a master thesis project at Chalmers University of Technology. The purpose of the thesis is to map and evaluate methods for skill assessment and to explore how employees' needs for upskilling and reskilling can be identified, with a focus on the battery industry. Your responses will be treated confidentially. Only individuals involved in the thesis project—such as myself as the student and my supervisors—will have access to the collected data. The data will be anonymized at the conclusion of the study. The results will be presented in the thesis, where no individual participants can be identified. You can read more detailed information about the study and data handling here:

https://chalmers-my.sharepoint.com/my?id=%2Fpersonal%2Fidawac%5Fchalmers%5Fse%2FDocuments%2FConsent%20for%20student%20thesis%2Epdf&parent=%2Fpersonal%2Fidawac%5Fchalmers%5Fse%2FDocuments

1. I have read the information and consent to participate in the master thesis project.

◯ Yes

Personal information

2. Name *

3. How old are you?

- 18–24
- 25–34
- 35–44
- 45-54
- 55 or older

4. Gender

- Man
- Woman
- Non-binary
- Prefer not to say
- Annat

Self-Assessment of Skills

In this section, you will assess your ability to perform various work tasks and follow specific work methods.
You will be presented with a number of statements and asked to rate the extent to which you agree with them.
Try to answer based on your immediate impression and do not spend too much time on each question. **If you are unfamiliar with what is described in the statement, you should answer "Do not agree at all."**

5. Applying and Following Standardized Work Methods

	Strongly dissagree	Dissagree	Neither agree nor disagree	Agree	Strongly agree
I am able to work according to standardized work methods (e.g., Lean, 5S, Six Sigma).	○	○	○	○	○
I understand the relationship between following standardized work methods and ensuring quality and efficiency.	○	○	○	○	○

6. Calculating and Comprehending Key Performance Index (KPI) and Parameters

	Strongly dissagree	Dissagree	Neither agree nor disagree	Agree	Strongly Agree
I can interpret key figures and parameters (e.g., temperature, pressure, viscosity, density).	○	○	○	○	○
I can calculate key figures and parameters (e.g., temperature, pressure, viscosity, density).	○	○	○	○	○

7. Equipment Maintenance

	Strongly dissagree	Dissagree	Neither agree nor disagree	Agree	Strongly Agree
I can clean equipment and machines properly to avoid contamination.	○	○	○	○	○
I can perform basic maintenance on the machines I work with.	○	○	○	○	○

8. Collaboration, Communication, and Teamwork

	Strongly disagree	Dissagree	Neither agree nor disagree	Agree	Strongly Agree
I can communicate effectively with colleagues.	◯	◯	◯	◯	◯
I am happy to assist my colleagues.	◯	◯	◯	◯	◯
I am not afraid to ask for help when I feel I need it.	◯	◯	◯	◯	◯

9. Curiosity and Lifelong Learning

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I actively seek opportunities to develop my skills and knowledge.	◯	◯	◯	◯	◯
I am open to adapting to changes in my professional role.	◯	◯	◯	◯	◯

10. Detecting Defective Products

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I can check the quality of products or processes.	◯	◯	◯	◯	◯
I can identify defects in products (e.g., bubbles, cracks, irregularities).	◯	◯	◯	◯	◯

11. Documentation and Monitoring of Production Data

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I can document my work in writing.	◯	◯	◯	◯	◯

12. Precision and Focus

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I can maintain focus on monotonous tasks during a workday	◯	◯	◯	◯	◯
I can work with processes that require precision and accuracy.	◯	◯	◯	◯	◯

13. Following Work Instructions and Recipes

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I can read and understand written work instructions.	◯	◯	◯	◯	◯
I can listen to and understand verbal work instructions.	◯	◯	◯	◯	◯

14. Handling Sensitive Materials, Equipment, and Products

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I can follow safety regulations when handling sensitive materials and products.	◯	◯	◯	◯	◯
I know how to handle sensitive materials and products to avoid damage or contamination.	◯	◯	◯	◯	◯

15. Using and Operating Machines

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I can work with and operate production machines.	○	○	○	○	○
I can make simple adjustments and settings on a machine when needed.	○	○	○	○	○

16. Performing Product Sampling

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly Agree
I can perform product sampling according to instructions to check quality.	○	○	○	○	○

17. Thinking Sequentially

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I understand how my work affects other parts of the production process.	○	○	○	○	○

18. Troubleshooting and Problem Solving

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Stongly Agree
I can troubleshoot processes and identify causes of problems.	○	○	○	○	○
I know when to solve a problem myself and when to ask for help.	○	○	○	○	○

19. Using Personal Protective Equipment (PPE)

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I know how to use personal protective equipment (e.g., gloves, safety glasses, protective clothing).	◯	◯	◯	◯	◯
When safety regulations require PPE, I comply.	◯	◯	◯	◯	◯

Work Experience and Education

20. What is your current employment status?

- Full-time employed
- Part-time employed
- Not employed, seeking work
- Not employed, not seeking work
- Student
- Student and working part-time
- Student and working full-time

21. 21. What is your highest level of education? If you are a student, indicate your current level.

- Primary school
- Upper secondary education (or equivalent)
- Vocational education
- University/College
- Annat

22. What have you studied (or what are you currently studying if you are still a student)?

23. Which sectors have you worked in previously?

- [ ] Healthcare and social care (healthcare, elderly care, home care)
- [ ] Retail and service (store, customer service, hotel, restaurant)
- [ ] Industry and production (manufacturing, assembly, quality control)
- [ ] Construction and civil engineering (carpentry, electrical, plumbing, road and building projects)
- [ ] Transport and logistics (warehouse, distribution, driver)
- [ ] IT and technology (programming, IT support, technical service)
- [ ] Education and research (teacher, supervisor, academic research)
- [ ] Agriculture, forestry, and fishing (cultivation, animal care, forestry)Agriculture, forestry, and fishing (cultivation, animal care, forestry)
- [ ] Public administration (municipality, government agency, state service)
- [ ] Annat

24. What have your main tasks been in your previous jobs?

C

Appendix: Coded Data Extraction Form

Table C.1: Skills Assessment Literature Overview

Resource	Ref.	Literature Type	Findings	Quality Note
Measuring skills in Europe	[69]	Journal article / Study	Skills measurement includes self-reports of job tasks, observation of task performance, and three key dimensions: uncertainty, autonomy, and continuous skill-building.	Uses survey data across 29 countries. Robust correlations tested, but relies on self-reporting. Moderate authority and evidence, limited objectivity due to method bias.
Measuring Skills in Developing Countries	[70]	Report / Methodology Guide	Measures skills using a mix of cognitive tests, self-reported job tasks, and employer surveys, covering both mental and socio-emotional (soft) skills.	Combines direct assessment with self-reports. Strong design and reputable source; applicability across countries limited by cultural/contextual factors.

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Table C.1: Skills Assessment Literature Overview (Continued)

Re-skilling for the Digital Humanities	[97]	Journal Article / Case Study	Describes a project-based training program assessed through self-reflections, work engagement surveys, and peer assessments; found effective for developing digital humanities skills.	Uses self- and peer-assessment plus engagement scales. Well-structured but based on a single case; generalizability limited.
Effectiveness of Collaboration in VET: Measuring Skills for Solving Complex Vocational Problems With a Multidimensional Authentic Technology-Based Assessment	[71]	Journal Article / Empirical Study	Measures skills using a multidimensional, technology-based assessment embedded in a business simulation, capturing both cognitive (problem-solving) and social (collaborative) skills through authentic vocational tasks in individual and collaborative settings.	Simulation-based assessment with computer agents. Strong design and clarity; relies on technology that may limit real-world transferability.
Managing Skills and Knowledge Using Online Tools	[72]	Journal Article / Practical Study	Measures skills and knowledge using online tools for mapping, self-assessment, and gap analysis, combining employee self-reports and manager reviews to target skills development.	Practical experience-based; includes managerial input. Applicable in industry but lacks empirical validation; limited scope.

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Table C.1: Skills Assessment Literature Overview (Continued)

Improving a self-assessment tool to monitor generic skills development in an active learning environment	[73]	Journal Article / Experimental Study	Measures generic skills using a self-assessment tool focused on skills like teamwork, communication, and critical thinking; tested new vs. old tool versions to improve accuracy and reflection. External experts were referenced to give their opinions on self-evaluations.	Tool revision improved self-reflection. Mixed validation and generalizability concerns; relies on self and mentor ratings.
The Role of Self-Assessment in Measuring Skills	[74]	Working Paper	Measures skills through graduate self-assessment of skill levels and job requirements, aiming to capture mismatches and skill use. Highlights both strengths and limitations of self-assessment (e.g., subjective bias) and contrasts it with objective assessments, which are seen as more reliable but costly and impractical for large-scale studies.	Widely cited review of skill metrics. Highlights trade-offs between subjective/objective tools; strong clarity and authority.

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Table C.1: Skills Assessment Literature Overview (Continued)

How to Verify and Measure Skills Development: The Value of Continuous Learning	[86]	Practitioner article	Discusses different methods for measuring skills pre- and post-training. Methods include performance reviews, certifications, training evaluations, and productivity analysis.	Industry-rooted, strategy-focused. Offers clear best practices but lacks academic rigor or external validation.
Measuring Skills at Work Lessons from the Field	[87]	Industry Report	Measures skills using multiple methods: training completion, pre/post knowledge tests, supervisor/manager observations with rubrics, credentialing, and performance assessments/simulations. Emphasizes integrating assessments into daily work, using frequent performance-based assessments, and tracking proficiency levels. Includes both objective and observational measures.	Highlights corporate use cases (e.g., IBM). Innovative but lacks broad implementation data and raises equity concerns.

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Table C.1: Skills Assessment Literature Overview (Continued)

Statistical approaches to the measurement of skills (Eurostat report)	[88]	Policy/Statistical Report	Describes European methods of measuring skills: (1) indirect (educational attainment, occupation); (2) direct (tests like PIAAC); (3) self-reported (task ability, job requirements). Covers dimensions: skills supply, demand, mismatch, and development. Emphasizes strengths of education-based data but highlights limits in capturing actual skills and relevance. Notes growing efforts in direct assessments and mixed methods but also gaps, especially in measuring skills mismatch and workplace skill development.	Reviews EU skill frameworks statistically. Strong authority and transparency; limited in-depth insights on advanced skill levels.

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Table C.1: Skills Assessment Literature Overview (Continued)

OECD Working Paper: Measures of Cognitive and Non-Cognitive Skills (EDU/WKP(2014)9)	[75]	Academic/Policy Working Paper	Reviews cognitive skills and non-cognitive skills. Discusses the challenges of self-reports (reference bias) and advocates for task-based and behavioral measures to capture skills. Shows that non-cognitive skills are predictive of life outcomes and can be measured via behaviors.	Conceptual framework with literature review. Advocates behavioral measures over self-reports; clear authority, limited empirical use.
Technical skill assessment in minimally invasive surgery using artificial intelligence: a systematic review	[76]	Systematic Review	Compares AI-driven methods (using video, kinematic, eye-tracking, fNIRS data) to classic expert observations for surgical skill assessment. Highlights limitations of traditional observation (subjective, inconsistent, time-consuming) vs. AI (objective, scalable).	Systematic review of simulator-based studies. Good structure; generalizability limited due to lack of clinical trials.

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Table C.1: Skills Assessment Literature Overview (Continued)

Surgical instrument detection and tracking technologies: Automating dataset labeling for surgical skill assessment	[77]	Reviewed article	The article highlights that traditional surgical skill assessment methods are inherently subjective, labor-intensive, and costly. In contrast, AI-driven approaches—particularly those leveraging video analysis and instrument tracking—aim to provide objective, automated, and scalable alternatives.	AI-focused detection methods review. Technical clarity and relevance to surgical training; simulation-focused, limited real-world application.
Procedural surgical skill assessment in laparoscopic training environments	[78]	Reviewed article	The study used computer-assisted Surgical Process Modeling (SPM) to assess laparoscopic skills by analyzing video recordings of a standardized suturing task. Experts showed fewer actions, shorter durations, and less idle time than novices, indicating more efficient and purposeful performance. The method enabled objective, detailed comparisons of surgical behavior based on annotated activity data.	SPM tool analysis in laparoscopy. Provides practical insights; supports training feedback but lacks broader testing.

Continued on next page

Table C.1: Skills Assessment Literature Overview (Continued)

Cognitive and Technical Skill Assessment in Surgical Education: a Changing Horizon	[79]	Narrative Review	The article outlines that traditional surgical assessment methods—such as written exams, oral evaluations, and in-training reports—are widely used but often subjective, limited in scope, and lack real-time performance insight. In contrast, newer methods offer structured and objective evaluations of both cognitive and technical skills. These include timed tasks, standardized checklists, and assessments by multiple trained observers, often conducted in simulated or controlled environments.	Narrative review of surgical assessments. Well-structured but lacks primary data and systematic rigor.

Continued on next page

Table C.1: Skills Assessment Literature Overview (Continued)

Specifying Criteria for the Assessment of Speaking Skill	[80]	Peer-reviewed journal article	The article proposes that speaking skill assessment should be based on structured criteria developed through expert analysis. It emphasizes the use of analytic rating scales or checklists that evaluate specific skills. The approach is firmly manual and rubric-based, relying on teacher expertise.	Peer-reviewed, theoretical article. Clear authority; no empirical testing; recommendations are literature-based.
Observational tools for assessment of procedural skills: a systematic review	[81]	Peer-reviewed journal article	This review analyzed observational tools for assessing surgical procedural skills, categorizing them into global rating scales, task-specific tools, and hybrids. Most methods rely on structured checklists and expert observation—either live or via video—and frequently involve multiple assessors to ensure reliability. While these tools showed validity at trainee level, they lacked standardization and rigorous validation at the specialist level.	PRISMA-based tool review. Validity and reliability addressed, but impact and specialist application underexplored.

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Table C.1: Skills Assessment Literature Overview (Continued)

Assessment in and of Serious Games: An Overview	[82]	Peer-reviewed journal article	The article highlights a variety of assessment methods in serious games, including traditional tools like pre/post-tests and questionnaires, alongside integrated techniques such as in-game tracking (stealth assessment), level-up testing, and behavior logs. It also explores emerging approaches like physiological monitoring (e.g., EEG, heart rate) to gauge engagement. The emphasis is on embedding assessment within gameplay to provide real-time feedback and adapt learning experiences.	Serious games assessment review. Broad, descriptive; limited empirical rigor or validation across tools.

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Table C.1: Skills Assessment Literature Overview (Continued)

Technical skill training and assessment in dental education	[83]	Peer-reviewed narrative review	Assesses technical skills through observational methods using rubrics, checklists, and structured rating scales, combined with physical simulators, digital tools (VR/AR), and workplace-based assessments to ensure objective and multidimensional evaluation of clinical competencies.	Narrative overview. Useful for orientation but lacks methodological depth and critical evaluation.
Performance metrics in mastoidectomy training: a systematic review	[84]	Peer-reviewed systematic review article	Uses computer-based VR simulation to assess surgical skills through metrics like time, force near structures, and efficiency. Methods include simulator-based observation with quantitative performance data and comparisons across experience levels.	Systematic review with strong methodology. High variability across studies limits generalizability.

Continued on next page

Table C.1: Skills Assessment Literature Overview (Continued)

Artificial Intelligence to Support the Training and Assessment of Professionals: A Systematic Literature Review	[85]	Peer-reviewed journal article	AI-based systems are proposed to supplement or replace human expert observations in professional training and assessment, particularly in hands-on fields like surgery. These systems aim to offer scalable, real-time, and objective feedback, overcoming the limitations of expert availability. While human observation is foundational (e.g., rule-based systems), most methods rely on sensor data and AI models rather than direct expert evaluation.	Policy review of emerging tools. Identifies gaps; strong analysis but limited real-world readiness.
Skills Assessment for Trade Occupations	[91]	Official government-recognized assessment framework (policy/practice documentation).	Uses a staged assessment approach combining documentary review, technical interviews, and practical demonstrations to evaluate trade knowledge, prior experience, and hands-on competence.	Australian trade skill assessment. Official, standardized, widely implemented. Strong authority and applicability.

Continued on next page

Table C.1: Skills Assessment Literature Overview (Continued)

Discover Your Skills and Careers	[89]	Government-endorsed digital career assessment tool.	Utilizes a 40-question multiple-choice assessment to evaluate user interests and motivations. Employs a standardized questionnaire focusing on self-reported preferences and strengths.	UK National Careers Service tool. Backed by government; meets advisory standards. Limited validation data.
Test your digital skills!	[90]	Official EU digital self-assessment tool.	Uses a self-assessment questionnaire based on the European Digital Competence Framework (DigComp), evaluating five core areas of digital competence. Includes both reflective and factual multiple-choice questions to assess real digital task performance and knowledge. Structured questionnaire format based on DigComp standards, ensuring consistency and comparability in assessing digital skills. Uses defined indicators and scoring guidelines.	EU Digital Skills tool. Commission-supported, widely accessible. Aligned with EU strategic goals; practical use emphasized.

D
Appendix: Observation Protocol

Observationsprotokoll Mixing

Generell Information

- **Observatör Namn:**____
- **Datum:**____
- **Deltagare 1:**____
- **Deltagare 2:**____
- **Deltagare 3:**____

Att hålla koll på under hela labben:

Deltagarna kommunicerad utan att större missförstånd uppstod: ☐ JA ☐NEJ

Uppstod det problem under labben: ☐ JA ☐NEJ

Deltagarna försökte själva lösa problemen innan de bad om hjälp: ☐ JA ☐NEJ

Hur många gånger bad de om hjälp under labben:__________________________

Kommentar från observatör (fylls i efter labb):

Bad deltagarna om hjälp för tidigt eller för sent? Var städningen av stationen noggrant eller slarvigt utförd? Kommentera gärna om deltagarna städade under arbetets gång samt om det fanns några oklarheter eller något du som observatör kan ha missat.

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PPE, skyddsutrustning – observera om deltagarna tar på sig det korrekt och om de använder det rätt under passet. Fyll i separat för deltagare 1 och deltagare 2.

Person 1	Tog på sig PPE korrekt		Använde PPE korrekt på sig under hela passet	
	JA	NEJ	JA	NEJ
Förkläde				
Handskar				
Skyddsglasögon				
Person 2	Tog på sig PPE korrekt		Använde PPE korrekt på sig under hela passet	
	JA	NEJ	JA	NEJ
Förkläde				
Handskar				
Skyddsglasögon				
Person 3	Tog på sig PPE korrekt		Använde PPE korrekt på sig under hela passet	
	JA	NEJ	JA	NEJ
Förkläde				
Handskar				
Skyddsglasögon				

Blandning av slurry:

	Korrekt utfört initialt		
Moment	JA	NEJ	Kommentar från observatör
Steg 5: Deltagarna tog fram SOP för vågen			
Steg 5: om vågen kalibrerades var det inga händer på arbetsstationen under tiden			

Steg 7: Vågen nollställdes			
Steg 8: **40 g** aktivt material mättes upp			
Steg 12: Slickepott användes			
Steg 13-26: Vid mixning var inga redskap eller fingrar i bunken			
Steg 13-26: Om material fastnade på kanterna användes slickepotten			
Steg 13: Mixern startades på nivå 12			
Steg 16: Vid hantering av pipettspetsen togs den med micropipetten			
Steg 16: Deltagarna upprepade steget 3 gånger			
Steg 25: vispen ställs på en servett på bordet			

Kvalitetsprov 2-4

	Korrekt utfört initialt		
Moment	JA	NEJ	Kommentar från observatör
Kvalitetsprov 2 - Steg 1: Bägaren kontrolleras enligt instruktion			
Kvalitetsprov 2 - Steg 3: Deciliter måttet lades undan på en servett			
Kvalitetsprov 3- Steg 5: PH-mätare startades ej innan detta steget			
Kvalitetsprov 3- Steg 10: Utfördes enligt beskrivning			

Kvalitetsprov 3- Steg 11: Utfördes enligt beskrivning			
Kvalitetsprov 4- Steg 2: Propellen var under slurryns yta			

Rengöring

Efter avslutat arbete vid stationen rengörs stationen ☐ JA ☐NEJ

Observationsprotokoll Calendering

Generell Information

- **Observatör Namn:**____
- **Datum:**____
- **Deltagare 1:**____
- **Deltagare 2:**____
- **Deltagare 3:**____

Att hålla koll på under hela labben:

Deltagarna kommunicerad utan att större missförstånd uppstod: ☐ JA ☐NEJ

Uppstod det problem under labben: ☐ JA ☐NEJ

Deltagarna försökte själva lösa problemen innan de bad om hjälp: ☐ JA ☐NEJ

Hur många gånger bad deltagarna om hjälp under labben:____________________

Kommentar från observatör (fylls i efter labb):

Bad deltagarna om hjälp för tidigt eller för sent? Var städningen av stationen noggrant eller slarvigt utförd? Kommentera gärna om deltagarna städade under arbetets gång samt om det fanns några oklarheter eller något du som observatör kan ha missat.

PPE, skyddsutrustning – observera om deltagarna tar på sig det korrekt och om de använder det rätt under passet. Fyll i separat för deltagare 1 och deltagare 2.

Person 1	Tog på sig PPE korrekt		Använde PPE korrekt på sig under hela passet	
	JA	NEJ	JA	NEJ
Handskar				
Skyddsglasögon				
Förkläde				
Person 2	Tog på sig PPE korrekt		Använde PPE korrekt på sig under hela passet	
	JA	NEJ	JA	NEJ
Handskar				
Skyddsglasögon				
Förkläde				
Person 3	Tog på sig PPE korrekt		Använde PPE korrekt på sig under hela passet	
	JA	NEJ	JA	NEJ
Handskar				
Skyddsglasögon				
Förkläde				

Pre-press:

	Korrekt utfört initialt		
Moment	JA	NEJ	Kommentar från observatör
Steg 3: En servett lades på vågen			
Steg 3: Vågen nollställdes			
Steg 3: **70 g** lera vägdes upp			
Steg 4: Först plattades leran ut med händerna			
Steg 4: Sedan användes kaveln för att platta ut			
Steg 4: Laminatet låg på leran när tjockleken mättes			

Press:

	Korrekt utfört initialt		
Moment	JA	NEJ	Kommentar från observatör
Steg 1: Valsavståndet ställdes in på 0			
Steg 2: När elektroden fördes igenom valsarna var pilarnas riktning uppåt			
Steg 3: Provet kördes igenom minst 2 gånger på samma valsavstånd			
Steg 3: Laminatet låg på leran vid mätning av tjockleken			
Steg 4: Överflödigt material skars bort **med skrapan**			
Steg 4: Överflödigt material sparades i en separat hög			

Rengöring

Efter avslutat arbete vid stationen rengörs stationen ☐ JA ☐NEJ

Observationsprotokoll Slitting

Generell Information

- **Observatör Namn:**____
- **Datum:**____
- **Deltagare 1:**____
- **Deltagare 2:**____
- **Deltagare 3:**____

Att hålla koll på under hela labben:

Deltagarna kommunicerad utan att större missförstånd uppstod: ☐ JA ☐NEJ

Uppstod det problem under labben: ☐ JA ☐NEJ

Deltagarna försökte själva lösa problemen innan de bad om hjälp: ☐ JA ☐NEJ

Hur många gånger bad deltagarna om hjälp under labben:____________________

Kommentar från observatör (fylls i efter labb):

Bad deltagarna om hjälp för tidigt eller för sent? Var städningen av stationen noggrant eller slarvigt utförd? Kommentera gärna om deltagarna städade under arbetets gång samt om det fanns några oklarheter eller något du som observatör kan ha missat.

PPE, skyddsutrustning – observera om deltagarna tar på sig det korrekt och om de använder det rätt under passet. Fyll i separat för deltagare 1 och deltagare 2.

Person 1	Tog på sig PPE korrekt		Använde PPE korrekt på sig under hela passet	
	JA	NEJ	JA	NEJ
Handskar				
Skyddsglasögon				
Person 2	Tog på sig PPE korrekt		Använde PPE korrekt på sig under hela passet	
	JA	NEJ	JA	NEJ
Handskar				
Skyddsglasögon				
Person 3	Tog på sig PPE korrekt		Använde PPE korrekt på sig under hela passet	
	JA	NEJ	JA	NEJ
Handskar				
Skyddsglasögon				

Skära elektroder:

Skriv vilken ordning deltagarna arbetar med följande material:

Wellpapp:__________

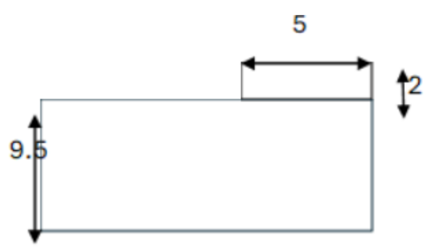
Al-folie:____________

A4 papper:________________

Kraftpapper:______________

För **wellpappen** utförs följande:

	Korrekt utfört initialt		
Moment	JA	NEJ	Kommentar från observatör
Steg 4: När steg 4 är klart, så fälls giljotinen ned			
Steg 5: Överflödet slängs i markerad låda			
Steg 7: Deltagarna **mäter** ut en flik			
Steg 8: Materialet klipps enligt instruktion			



Materialet ska se ut så här efter klippning!

För **Kraftpapperet** utförs följande:

	Korrekt utfört initialt		
Moment	JA	NEJ	Kommentar från observatör
Steg 5: När steg 5 är klart, så fälls giljotinen ned			
Steg 6: Överflödet slängs enligt instruktion			
Steg 8: Deltagarna **mäter** ut en flik			
Steg 9: Materialet klipps enligt instruktion			

Observationsprotokoll Cell finishing

Generell Information

- **Observatör Namn:**______________________________
- **Datum:**______________________________
- **Deltagare 1:**______________________________
- **Deltagare 2:**______________________________
- **Deltagare 3:**______________________________

Att hålla koll på under hela labben:

Deltagarna kommunicerad utan att större missförstånd uppstod: ☐ JA ☐NEJ

Uppstod det problem under labben: ☐ JA ☐NEJ

Deltagarna försökte själva lösa problemen innan de bad om hjälp: ☐ JA ☐NEJ

Hur många gånger bad deltagarna om hjälp under labben:______________

Kommentar från observatör (fylls i efter labb):

Bad deltagarna om hjälp för tidigt eller för sent? Var städningen av stationen noggrant eller slarvigt utförd? Kommentera gärna om deltagarna städade under arbetets gång samt om det fanns några oklarheter eller något du som observatör kan ha missat.

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PPE, skyddsutrustning – observera om deltagarna tar på sig det korrekt och om de använder det rätt under passet. Fyll i separat för deltagare 1 och deltagare 2.

Person 1	Tog på sig PPE korrekt		Använde PPE korrekt på sig under hela passet	
	JA	NEJ	JA	NEJ
Handskar				
Skyddsglasögon				
Person 2	Tog på sig PPE korrekt		Använde PPE korrekt på sig under hela passet	
	JA	NEJ	JA	NEJ
Handskar				
Skyddsglasögon				
Person 3	Tog på sig PPE korrekt		Använde PPE korrekt på sig under hela passet	
	JA	NEJ	JA	NEJ
Handskar				
Skyddsglasögon				

Test av Multimeter

	Korrekt utfört initialt		
Moment	JA	NEJ	Kommentar från observatör
Steg 4. Multimetern ställdes **direkt** in på likspänning			
Steg 5. Svart prob fästes på 9V batteriets negativa pol			
Steg 6. Röd prob fästes på 9V batteriets positiva pol			
Steg 8. OK/NOK registrerades i protokollet			

1.2 Mätning av battericell

	Korrekt utfört initialt		
Moment	JA	NEJ	Kommentar från observatör
Steg 1. Svart prob fästes på battericell 1:s negativa pol			
Steg 2. Röd prob fästes på battericell 1:s positiva pol			
Steg 3-4. Värde på multimetern avlästes och registrerades i protokollet			

Rengöring

Efter avslutat arbete vid stationen rengörs stationen ☐ JA ☐NEJ

Observationsprotokoll BPT

Generell Information

- **Observatör Namn:**____
- **Datum:**____
- **Deltagare 1 (för- och efternamn):**______________________________
- **Deltagare 2(för- och efternamn):**______________________________

Fyll i efter labben:

Produkter:__________ OPR:______________

Att hålla koll på under hela labben:

1.1 Deltagarna kommunicerad utan att större missförstånd uppstod: ☐ JA ☐NEJ

1.2 Uppstod det problem under labben: ☐ JA ☐NEJ

1.3 Deltagarna försökte själva lösa problemen innan de bad om hjälp: ☐ JA ☐NEJ

1.4 Hur många gånger bad de om hjälp under labben:________________

1.5 Hur många gånger användes andon knappen:____________________

1.6 Hur många gånger hanterade deltagare 1 power lock out låsen felaktigt:_________

1.7 Hur många gånger hanterade deltagare 2 power lock out låsen felaktigt:_________

Kommentar från observatör (fylls i efter labb):

Upplevde du att deltagarna bad om hjälp för sent? Hjälpte dem varandra? Upplevde du som observatör att det var någon skillnad i vem av deltagarna som kunde mest? Alla kommentarer är välkomna.

Observations protokoll för fel nr. 1

		Korrekt utfört initialt		
Moment	Tid	JA	NEJ	Kommentar från observatör
Produktion startas (grön knapp)				
Fel uppkommer (röd markering HMI)				
Deltagare har navigerat till felet				
Deltagarna begär tillträde				
Första säkerhetslåset har monterats				
Andra säkerhetslåset har monterats				
Lösningsarbete klart.				
Deltagare stänger dörren till produktionscellen				
Problem korrekt avhjälpt				
Återställning genomförts (gul knapp och blå knapp)				
Produtkion startas				

Observations protokoll för fel nr. 2

		Korrekt utfört initialt		
Moment	Tid	JA	NEJ	Kommentar från observatör
Fel uppkommer (röd markering HMI)				
Deltagare har navigerat till felet				
Deltagarna begär tillträde				
Första säkerhetslåset har monterats				
Andra säkerhetslåset har monterats				
Lösningsarbete klart.				
Deltagare stänger dörren till produktionscellen				
Problem korrekt avhjälpt				
Återställning genomförts (gul knapp och blå knapp)				
Produtkion startas				

Observations protokoll för fel nr. 3

		Korrekt utfört initialt		
Moment	Tid	JA	NEJ	Kommentar från observatör
Fel uppkommer (röd markering HMI)				
Deltagare har navigerat till felet				
Deltagarna begär tillträde				
Första säkerhetslåset har monterats				
Andra säkerhetslåset har monterats				
Lösningsarbete klart.				
Deltagare stänger dörren till produktionscellen				
Problem korrekt avhjälpt				
Återställning genomförts (gul knapp och blå knapp)				
Produtkion startas				

Observations protokoll för fel nr. 4

		Korrekt utfört initialt		
Moment	Tid	JA	NEJ	Kommentar från observatör
Fel uppkommer (röd markering HMI)				
Deltagare har navigerat till felet				
Deltagarna begär tillträde				
Första säkerhetslåset har monterats				
Andra säkerhetslåset har monterats				
Lösningsarbete klart.				
Deltagare stänger dörren till produktionscellen				
Problem korrekt avhjälpt				
Återställning genomförts (gul knapp och blå knapp)				
Produtkion startas				

Observations protokoll för fel nr. 5

		Korrekt utfört initialt		
Moment	Tid	JA	NEJ	Kommentar från observatör
Fel uppkommer (röd markering HMI)				
Deltagare har navigerat till felet				
Deltagarna begär tillträde				
Första säkerhetslåset har monterats				
Andra säkerhetslåset har monterats				
Lösningsarbete klart.				
Deltagare stänger dörren till produktionscellen				
Problem korrekt avhjälpt				
Återställning genomförts (gul knapp och blå knapp)				
Produtkion startas				

Observations protokoll för fel nr. 6

		Korrekt utfört initialt		
Moment	Tid	JA	NEJ	Kommentar från observatör
Fel uppkommer (röd markering HMI)				
Deltagare har navigerat till felet				
Deltagarna begär tillträde				
Första säkerhetslåset har monterats				
Andra säkerhetslåset har monterats				
Lösningsarbete klart.				
Deltagare stänger dörren till produktionscellen				
Problem korrekt avhjälpt				
Återställning genomförts (gul knapp och blå knapp)				
Produtkion startas				

Observations protokoll för fel nr. 7

		Korrekt utfört initialt		
Moment	Tid	JA	NEJ	Kommentar från observatör
Fel uppkommer (röd markering HMI)				
Deltagare har navigerat till felet				
Deltagarna begär tillträde				
Första säkerhetslåset har monterats				
Andra säkerhetslåset har monterats				
Lösningsarbete klart.				
Deltagare stänger dörren till produktionscellen				
Problem korrekt avhjälpt				
Återställning genomförts (gul knapp och blå knapp)				
Produtkion startas				

Observations protokoll för fel nr. 8

		Korrekt utfört initialt		
Moment	Tid	JA	NEJ	Kommentar från observatör
Fel uppkommer (röd markering HMI)				
Deltagare har navigerat till felet				
Deltagarna begär tillträde				
Första säkerhetslåset har monterats				
Andra säkerhetslåset har monterats				
Lösningsarbete klart.				
Deltagare stänger dörren till produktionscellen				
Problem korrekt avhjälpt				
Återställning genomförts (gul knapp och blå knapp)				
Produtkion startas				

E

Appendix: Trainers' Evaluation Form

Trainer utvärdering – BST

Trainers utvärdering av deltagarna för att kartlägga skills

Som trainer ombeds du fylla i denna utvärdering så nära anslutning till labben som möjligt, baserat på dina åsikter och observationer.

Namn trainer: ________________________

Notera namnen på de deltagarna du har arbetat med.

Station	**Deltagare**	**Station**	**Deltagare**
	Deltagare 1		Deltagare 2
	Deltagare 3		Deltagare 4
	Deltagare 5		Deltagare 6
	Deltagare 7		Deltagare 8
	Deltagare 9		Deltagare 10
	Deltagare 11		Deltagare 12
	Deltagare 13		Deltagare 14
	Deltagare 15		Deltagare 16

Skattning av skills för deltagare

Som trainer ska du skatta deltagarens färdigheter och kryssa i rutan beroende på hur väl du instämmer med påståendena nedan.

Skala:

1. Instämmer inte alls
2. Instämmer inte
3. Varken instämmer eller instämmer inte
4. Instämmer
5. Instämmer helt

Vet ej (Om du inte kan göra en bedömning)

Deltagaren kan tillämpa och följa standardiserade arbetsmetoder

	1	2	3	4	5	Vet ej
Deltagare 1						
Deltagare 2						
Deltagare 3						
Deltagare 4						
Deltagare 5						
Deltagare 6						
Deltagare 7						
Deltagare 8						
Deltagare 9						
Deltagare 10						
Deltagare 11						
Deltagare 12						
Deltagare 13						
Deltagare 14						
Deltagare 15						
Deltagare 16						

Kommentar:

Deltagaren kan använda PPE på ett korrekt sätt

	1	2	3	4	5	Vet ej
Deltagare 1						
Deltagare 2						
Deltagare 3						
Deltagare 4						
Deltagare 5						
Deltagare 6						
Deltagare 7						
Deltagare 8						
Deltagare 9						
Deltagare 10						
Deltagare 11						
Deltagare 12						
Deltagare 13						
Deltagare 14						
Deltagare 15						
Deltagare 16						

Kommentar:

Deltagaren var nyfiken och ställde frågor

	1	2	3	4	5	Vet ej
Deltagare 1						
Deltagare 2						
Deltagare 3						
Deltagare 4						
Deltagare 5						
Deltagare 6						
Deltagare 7						
Deltagare 8						
Deltagare 9						
Deltagare 10						
Deltagare 11						
Deltagare 12						
Deltagare 13						
Deltagare 14						
Deltagare 15						
Deltagare 16						

Kommentar:

Deltagaren höll fokus under arbetspasset

	1	2	3	4	5	Vet ej
Deltagare 1						
Deltagare 2						
Deltagare 3						
Deltagare 4						
Deltagare 5						
Deltagare 6						
Deltagare 7						
Deltagare 8						
Deltagare 9						
Deltagare 10						
Deltagare 11						
Deltagare 12						
Deltagare 13						
Deltagare 14						
Deltagare 15						
Deltagare 16						

Kommentar:

Deltagaren kan beräkna och tolka nyckeltal

	1	2	3	4	5	Vet ej
Deltagare 1						
Deltagare 2						
Deltagare 3						
Deltagare 4						
Deltagare 5						
Deltagare 6						
Deltagare 7						
Deltagare 8						
Deltagare 9						
Deltagare 10						
Deltagare 11						
Deltagare 12						
Deltagare 13						
Deltagare 14						
Deltagare 15						
Deltagare 16						

Kommentar:

Deltagaren kan hantera utrustningen, maskiner, verktyg på ett korrekt och säkert sätt

	1	2	3	4	5	Vet ej
Deltagare 1						
Deltagare 2						
Deltagare 3						
Deltagare 4						
Deltagare 5						
Deltagare 6						
Deltagare 7						
Deltagare 8						
Deltagare 9						
Deltagare 10						
Deltagare 11						
Deltagare 12						
Deltagare 13						
Deltagare 14						
Deltagare 15						
Deltagare 16						

Kommentar:

Deltagaren kan rengöra utrustning på ett sätt som undviker kontaminering

	1	2	3	4	5	Vet ej
Deltagare 1						
Deltagare 2						
Deltagare 3						
Deltagare 4						
Deltagare 5						
Deltagare 6						
Deltagare 7						
Deltagare 8						
Deltagare 9						
Deltagare 10						
Deltagare 11						
Deltagare 12						
Deltagare 13						
Deltagare 14						
Deltagare 15						
Deltagare 16						

Kommentar:

Deltagaren försökte själva lösa problem som uppstod

	1	2	3	4	5	Vet ej
Deltagare 1						
Deltagare 2						
Deltagare 3						
Deltagare 4						
Deltagare 5						
Deltagare 6						
Deltagare 7						
Deltagare 8						
Deltagare 9						
Deltagare 10						
Deltagare 11						
Deltagare 12						
Deltagare 13						
Deltagare 14						
Deltagare 15						
Deltagare 16						

Kommentar:

Deltagaren kan utföra kvalitetskontroller

	1	2	3	4	5	Vet ej
Deltagare 1						
Deltagare 2						
Deltagare 3						
Deltagare 4						
Deltagare 5						
Deltagare 6						
Deltagare 7						
Deltagare 8						
Deltagare 9						
Deltagare 10						
Deltagare 11						
Deltagare 12						
Deltagare 13						
Deltagare 14						
Deltagare 15						
Deltagare 16						

Kommentar:

Deltagaren kan dokumentera resultat och processer

	1	2	3	4	5	Vet ej
Deltagare 1						
Deltagare 2						
Deltagare 3						
Deltagare 4						
Deltagare 5						
Deltagare 6						
Deltagare 7						
Deltagare 8						
Deltagare 9						
Deltagare 10						
Deltagare 11						
Deltagare 12						
Deltagare 13						
Deltagare 14						
Deltagare 15						
Deltagare 16						

Kommentar:

Deltagaren kan hantera känsliga material och utrustning

	1	2	3	4	5	Vet ej
Deltagare 1						
Deltagare 2						
Deltagare 3						
Deltagare 4						
Deltagare 5						
Deltagare 6						
Deltagare 7						
Deltagare 8						
Deltagare 9						
Deltagare 10						
Deltagare 11						
Deltagare 12						
Deltagare 13						
Deltagare 14						
Deltagare 15						
Deltagare 16						

Kommentar:

Deltagaren kan utföra provtagningar av produkter enligt instruktioner

	1	2	3	4	5	Vet ej
Deltagare 1						
Deltagare 2						
Deltagare 3						
Deltagare 4						
Deltagare 5						
Deltagare 6						
Deltagare 7						
Deltagare 8						
Deltagare 9						
Deltagare 10						
Deltagare 11						
Deltagare 12						
Deltagare 13						
Deltagare 14						
Deltagare 15						
Deltagare 16						

Kommentar:

Deltagaren förstår hur sitt arbete kan påverka andra delar av processen

	1	2	3	4	5	Vet ej
Deltagare 1						
Deltagare 2						
Deltagare 3						
Deltagare 4						
Deltagare 5						
Deltagare 6						
Deltagare 7						
Deltagare 8						
Deltagare 9						
Deltagare 10						
Deltagare 11						
Deltagare 12						
Deltagare 13						
Deltagare 14						
Deltagare 15						
Deltagare 16						

Kommentar:

Trainer utvärdering – BPT

Trainers utvärdering av deltagarna för att kartlägga skills

Som trainer ombeds du fylla i denna utvärdering så nära anslutning till runda 1 som möjligt, baserat på dina åsikter och observationer.

Namn trainer: ___________________________ Ifylld efter runda:_______

Notera namnen på de deltagarna du har arbetat med och markera sedan längre ner i dokumentet hur du skattar deras skills inom specifika områden

Deltagare 1:__________________________ Deltagare 2:____________________________

Deltagare 3:__________________________ Deltagare 4:____________________________

Deltagare 5:__________________________ Deltagare 6:____________________________

Deltagare 7:__________________________ Deltagare 8:____________________________

Deltagare 9:__________________________ Deltagare 10:___________________________

Skattning av skills för deltagare

Som trainer ska du skatta deltagarens färdigheter och kryssa i rutan beroende på hur väl du instämmer med påståendena nedan.
Skala:

1. Instämmer inte alls
2. Instämmer inte
3. Varken instämmer eller instämmer inte
4. Instämmer
5. Instämmer helt

Vet ej (Om du inte kan göra en bedömning)

Deltagaren kan tillämpa och följa standardiserade arbetsmetoder

	1	2	3	4	5	Vet ej
Deltagare 1						
Deltagare 2						
Deltagare 3						
Deltagare 4						
Deltagare 5						
Deltagare 6						
Deltagare 7						
Deltagare 8						
Deltagare 9						
Deltagare 10						

Kommentar:

Deltagaren kan kommunicera på ett bra och försåtligt sätt samt samarbetar

	1	2	3	4	5	Vet ej
Deltagare 1						
Deltagare 2						
Deltagare 3						
Deltagare 4						
Deltagare 5						
Deltagare 6						
Deltagare 7						
Deltagare 8						
Deltagare 9						
Deltagare 10						

Kommentar:

Deltagaren var nyfiken och ställde frågor

	1	2	3	4	5	Vet ej
Deltagare 1						
Deltagare 2						
Deltagare 3						
Deltagare 4						
Deltagare 5						
Deltagare 6						
Deltagare 7						
Deltagare 8						
Deltagare 9						
Deltagare 10						

Kommentar:

Deltagaren höll fokus under arbetspasset

	1	2	3	4	5	Vet ej
Deltagare 1						
Deltagare 2						
Deltagare 3						
Deltagare 4						
Deltagare 5						
Deltagare 6						
Deltagare 7						
Deltagare 8						
Deltagare 9						
Deltagare 10						

Kommentar:

Deltagaren kunde följa instruktioner såväl muntligt som skriftligt

	1	2	3	4	5	Vet ej
Deltagare 1						
Deltagare 2						
Deltagare 3						
Deltagare 4						
Deltagare 5						
Deltagare 6						
Deltagare 7						
Deltagare 8						
Deltagare 9						
Deltagare 10						

Kommentar:

Deltagaren kunde hantera utrustningen (boxen, HMI, knappar etc.) på ett bra sätt

	1	2	3	4	5	Vet ej
Deltagare 1						
Deltagare 2						
Deltagare 3						
Deltagare 4						
Deltagare 5						
Deltagare 6						
Deltagare 7						
Deltagare 8						
Deltagare 9						
Deltagare 10						

Kommentar:

Deltagaren följde säkerhetsföreskrifter (tex power lock out)

	1	2	3	4	5	Vet ej
Deltagare 1						
Deltagare 2						
Deltagare 3						
Deltagare 4						
Deltagare 5						
Deltagare 6						
Deltagare 7						
Deltagare 8						
Deltagare 9						
Deltagare 10						

Kommentar:

Deltagaren försökte själva lösa problem som uppstod

	1	2	3	4	5	Vet ej
Deltagare 1						
Deltagare 2						
Deltagare 3						
Deltagare 4						
Deltagare 5						
Deltagare 6						
Deltagare 7						
Deltagare 8						
Deltagare 9						
Deltagare 10						

Kommentar:

Deltagaren bad om hjälp vid rätt tidpunkt (väntade inte för länge och bad inte om hjälp bara för att)

	1	2	3	4	5	Vet ej
Deltagare 1						
Deltagare 2						
Deltagare 3						
Deltagare 4						
Deltagare 5						
Deltagare 6						
Deltagare 7						
Deltagare 8						
Deltagare 9						
Deltagare 10						

Kommentar:

F

Appendix: Results Grouped by Age

Table F.1, the evaluation scores are grouped into four age brackets: 18–24, 25–34, 35–44, and 45–54. Each group's average scores are presented for all three assessment methods: Self, Trainer, and Observer.

Table F.1: Mean Scores by Skill, Age, and Source

Skill	**Self**				**Trainer**				**Observer**			
	18–24	25–34	35–44	45–54	18–24	25–34	35–44	45–54	18–24	25–34	35–44	45–54
S1	4.6	4.5	4.6	4.4	4.2	3.9	3.9	4.0	3.6	3.1	3.3	3.1
S2	4.6	4.4	4.6	4.4	3.5	3.8	4.0	3.8	-	-	-	-
S3	4.4	4.2	4.3	4.2	3.7	3.8	3.7	3.5	3.3	3.1	3.3	3.1
S4	4.4	4.4	4.4	4.2	3.4	3.3	2.9	3.0	3.2	3.3	3.1	2.9
S5	4.6	4.3	4.2	4.3	3.2	3.0	4.0	4.3	4.2	3.4	4.1	4.0
S6	4.1	4.3	4.5	4.2	4.1	4.1	3.8	4.0	3.5	2.8	3.8	2.9
S7	3.5	3.5	3.9	3.2	3.8	3.9	3.7	3.8	1.7	1.4	3.0	1.0
S8	4.1	4.0	4.1	3.4	4.0	4.0	4.1	4.3	5.0	5.0	5.0	5.0
S9	4.2	4.0	4.0	4.0	4.4	4.4	4.2	4.6	3.4	2.8	3.8	3.0
S10	4.3	4.1	4.1	4.0	3.9	4.0	3.8	3.6	1.7	1.4	3.3	2.2
S11	4.3	4.1	4.4	3.8	4.1	4.3	4.1	4.2	2.7	3.0	3.1	2.4
S12	4.1	4.1	4.3	3.5	3.9	3.9	3.6	3.5	-	1.0	4.2	-
S13	3.9	3.4	4.2	3.3	4.0	4.0	4.0	4.3	-	-	-	-
S14	3.6	3.3	3.9	2.7	-	-	-	-	-	-	-	-
S15	3.4	3.3	3.6	2.7	3.2	3.0	4.0	4.0	4.2	3.4	4.1	4.0

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