

AI, human robot collaboration, and microrobotics for sustainable semiconductor manufacturing

Maryam B. Javareshk²[0000-0001-6068-4203], Tomasz Kołcon¹[0000-0003-0089-1512], Iveta Eimontaite²[0000-0002-8622-937X], Sarah Fletcher²[0000-0001-6606-7556], Jakub Bartkiewicz¹[0009-0002-3311-8008], Piotr Gemza¹[0000-0002-8456-414X], Krystian Gołowski³[0009-0002-6649-5889], Miron Kołodziejczyk¹[0009-0006-1480-9451], Adam Wołoszczuk¹[0000-0003-3794-9343]

¹ Łukasiewicz Research Network – Industrial Research Institute for Automation and Measurements PIAP, Al. Jerozolimskie 202, 02-486 Warsaw, Poland

[tomasz.kolcon,jakub.bartkiewicz,piotr.gemza,miron.kolodziejczyk,adam.woloszczuk}@piap.lukasiewicz.gov.pl](mailto:{tomasz.kolcon,jakub.bartkiewicz,piotr.gemza,miron.kolodziejczyk,adam.woloszczuk}@piap.lukasiewicz.gov.pl)

² Cranfield University, Cranfield, MK43 0AL, UK

{M.BathaeiJavareshk, iveta.eimontaite,sarah.fletcher}@cranfield.ac.uk

³ VIGO Photonics, Poznańska Street 129/133, 05-850 Ożarów Mazowiecki, Poland

kgolowski@vigo.com.pl

Abstract— This paper aims to show the efforts of the AI-PRISM Horizon Project for Semiconductors Pilot. Pilot is an example of the microscale positioning of semiconductor chips supported by AI. Usage of the stand is verified in the production environment. The second iteration of the assembly station is an effect of social aspect analysis. The collaboration and human acceptance of AI decision-making is validated in the infrared detectors production facility.

I. INTRODUCTION

The current study investigates the Human Robot Collaboration (HRC) and Artificial Intelligence (AI) solutions in small-scale electronics manufacturing, focusing on both technical challenges and human factors to ensure workforce acceptance and operational efficiency.

The main technical idea was to build an assembly station that would relieve the operator during manual, precise, but repeatable activities. The station consists of precise motorized XY stages, microscopic cameras and additional equipment [Fig. 1.] [Fig. 2.]. This allows for the automation of work, with improved accuracy and repeatability. In order to assess whether the above-mentioned results were achieved, experimental work was conducted. Furthermore, as part of the AI-PRISM project, a three-stage

operator engagement program was delivered to facilitate user involvement and improve system usability.

Stage 1: A hierarchical task analysis, combined with eye-tracking and interview data, identified key human factors, decision-making processes, and areas of cognitive strain during assembly tasks.

Stage 2: Interactive workshops enabled operators to discuss workflow challenges, envision future improvements, and provide feedback on the proposed AI-driven solution.

Stage 3: An on-site experiment compared the traditional and AI-assisted assembly processes, measuring physiological responses (electrodermal activity and heart rate) alongside self-reported workload assessments. .



Fig. 1. Assembly station – old solution

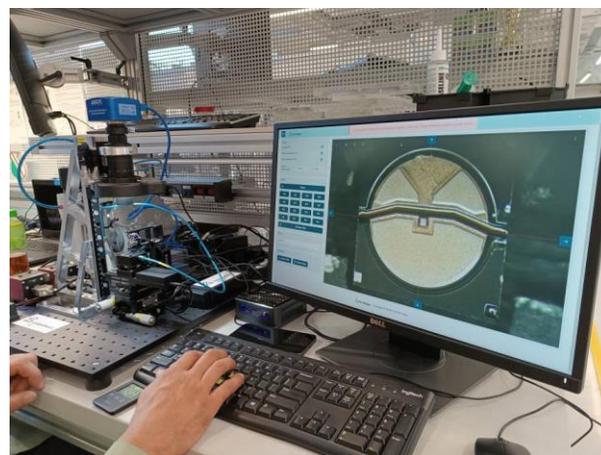


Fig. 2. Assembly station – new solution

II. CONTEXT AND MOTIVATION

There are several factors that made us decide to address the issue described:

- Robotics and AI are increasingly integrated into small-scale electronics manufacturing.

- High-precision assembly presents both technical challenges and human factors considerations.
- Ensuring workforce acceptance and operational efficiency is crucial for successful implementation.

Initial research conducted at the beginning of the project allowed us to identify the most labor-intensive and stressful stages of the entire process. Based on this research, we identified which activities could be relatively easily replaced by automatic solutions.

III. OBJECTIVE OF THE STUDY

Based on in-depth analysis, an assembly station was created. Manual tables were replaced with motorized ones with very high precision $<1\mu\text{m}$. The usual single camera was replaced with a digital microscope camera. Two additional ones were also added to improve the visibility of the work area. The whole system runs under the control of dedicated software. An AI-based module is responsible for the automatic positioning [4][5] due to the relatively large differences in view between individual chips. Keypoint detection techniques are used for positioning purposes. In addition, the AI module is used for defect detection [6], which also relieves the operator's workload.



Fig. 3. Defects detection

TABLE I. OLD AND NEW SOLUTION TECHNICAL COMPARISON

Feature/functionality	Comparison	
	Old solution	New solution
Positioning device	Manual XY translation stages	Motorized XY translation stages
Perception	One microscope	Three microscopic high resolution cameras
Calibration	Calibration must be performed manually for each single chip	Semi-automatic periodic calibration
Chips per device	One	4x4 matrix
Positioning procedure	Manually turn the knobs and observe	Chip selection, automatic positioning and

	the alignment on the screen	possible manual correction
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To verify whether the intended effects had been achieved, several activities were carried out:

- Investigate how operator engagement can facilitate smoother AI adoption.
- Assess human factors impact through a structured three-stage engagement program.
- Measure physiological and subjective responses to evaluate ease of use and workload differences.

IV. METHOD

Stage 1:

- Hierarchical task analysis and task decomposition
- Eye tracking observations
- Qualitative insights (interviews)

Stage 2:

- Participatory workshop with operators of varying process experience
- Prototype demonstration and feedback
- Current and future work visioning

Stage 3:

- Task execution & Eye-tracker measurement (traditional and AI-assisted methods)
- Physiological measurements (EDA& HR)
- Self-assessment Questionnaires (NASA TLX, System Usability Scale, User Experience Questionnaire)

V. RESULTS

A. Stage 1 (Task Analysis and Cognitive Load Assessment supported with eye-tracker data and interviews) [Fig. 4]

- Novice operator showed wider gaze spread and longer dwell times, especially on the microscope, indicating higher cognitive load.

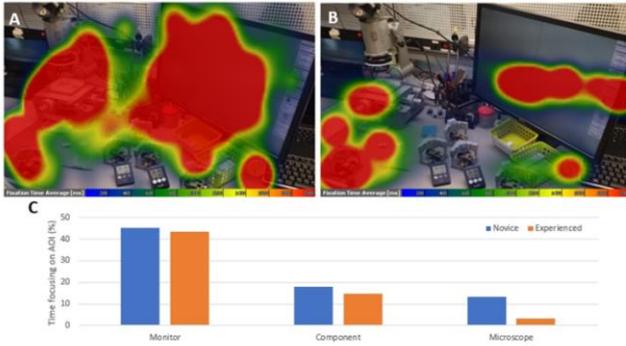


Fig. 4. Eye tracking heatmaps (A) Novice operator, (B), experienced) on three area of interest (C)

- Experienced operator focused on specific Areas of Interest (AOIs) and used tactile feedback for microscope adjustments without visual attention.
- Both operators indicated that the monitor required the most mental focus, while long screen exposure may contribute to eye strain.

B. Stage 2 (Interactive Operators' Workshop)

The discussion [Fig 5] outlined three key challenges operators face in the process:

- Microscope Calibration: Time-consuming and prone to errors.
- Gluing Process: Difficult to control glue quantity and positioning.
- Wire Bending Risk: Impacts product quality and reliability.

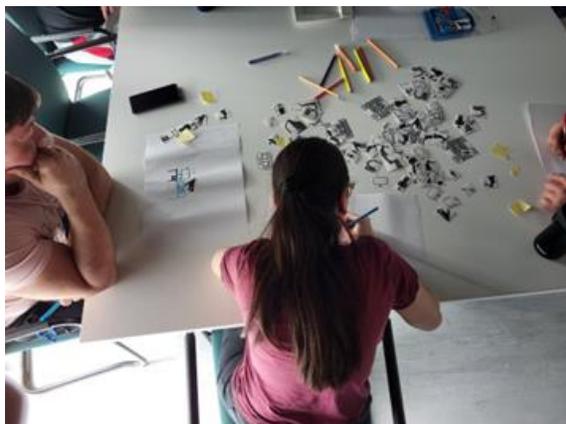


Fig. 5. Interactive workshop process



Fig. 6. solution designed by the operators in the workshop

Key Challenges:

- Proposed Solutions [Fig 6]:
- Robotic systems for positioning & calibration with operator oversight.
- Automated data sharing between machines for early error detection.
- Remote access to enhance flexibility and control.

C. Stage 3 (Experimental Evaluation Of AI-enabled Process)

The data collection with a small sample of operators (2 experienced and 2 novice) revealed several key findings:

- Operators spent less time monitoring the automation/microscope and chip assembly areas in the new process [Fig 7].

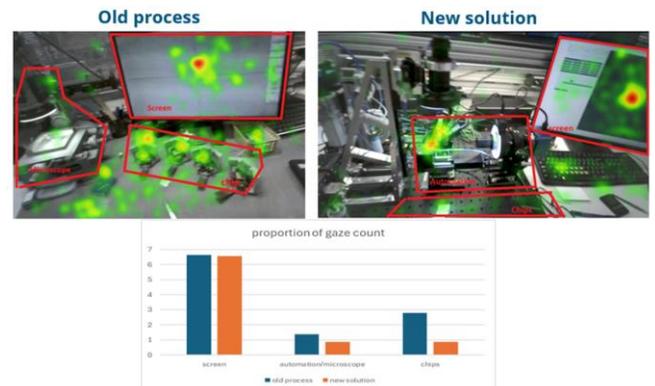


Fig. 7. Experimental Evaluation Of AI-enabled Process (eye gaze heatmaps)

- This is likely due to process changes: multiple chips are arranged at once and inspected automatically, whereas the old process required manual, visually demanding control
- The findings suggest lower mental demand and increased learnability, leading to a more sustainable process over time

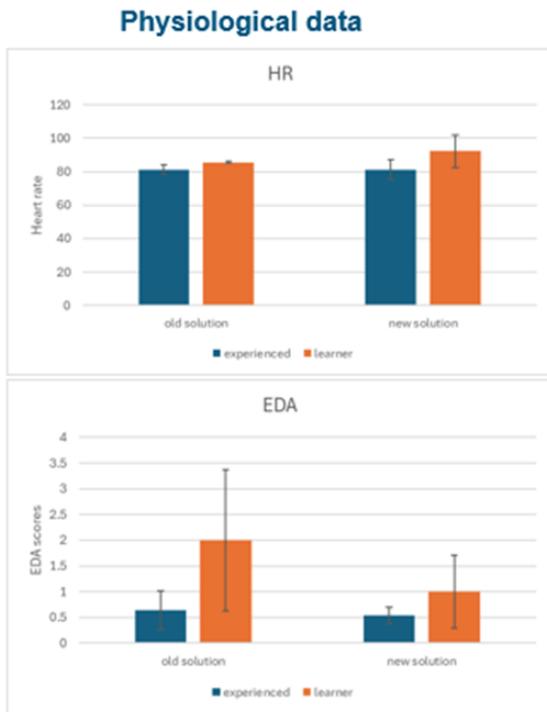


Fig. 8. Psychological data

- Physiological data showed lower electrodermal activity in the new solution, especially for learners.
- Heart rate (HR) remains similar across solutions, suggesting no changes in physical strain.
- Self-report data highlights lower mental, physical, and temporal demand in the new solution, supporting better usability and less cognitive strain.



Fig. 9. NASA-TLX task load self-assessment

VI. DISCUSSION AND CONCLUSION

Findings indicate that the new semi-automated process significantly reduces mental, physical, and temporal demand while supporting lower stress levels – particularly for learners. Decrease in stress can lead in a short-term towards maintaining

situational awareness and focus on the assembly directly impacting human error and production rates. In the long-term optimal stress levels are linked to greater wellbeing. This can affect less sickness days from the employees and, therefore, positively impact production rates. The combination of self-report data and physiological measures suggests that the new solution enhances usability, learnability, and overall operator well-being without increasing physical strain. These results emphasize the potential of AI-based automation to improve not only efficiency but also sustainability of human work in high-precision manufacturing.

Further research could explore:

- Long-term effects of the new process on operator performance and acceptance.
- The impact of AI explainability and trust on user experience.
- Broader implementation across different production tasks.
- Evaluation of collaborative human-AI decision-making scenarios.

AI positioning module be adapted for other precision manufacturing tasks beyond semiconductor assembly.

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