Advancing Manufacturing Maintenance with Mixed Reality: Integrating HoloLens 2 in the Siemens-Festo Cyber-Physical Factory

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***Abstract*—Globalisation and digitalisation are making digital transformation inevitable, and current workforce skills and artificial intelligence regulations are not ready for the demands of a new era of smart manufacturing. Alternatively, Mixed Reality (MR) technology, which integrates real-world and computer-generated environments, offers digital transformation support by providing immersive digital spaces with unique multimodal interactions. However, the maturity of MR technology requires enhancement, particularly in its software architecture for real manufacturing applications. This study demonstrates the implementation of HoloLens 2 MR interactions within the Siemens-Festo Cyber-Physical Factory system, specifically for the offset calibration of an infrared sensor. The developed software architecture, MR functionalities, and performance data obtained from the Unity profiler suggest that there are significant opportunities for software optimisation to achieve real-time and seamless data visualisation. However, the application-specific nature of the optimisation increases the dependence on software experts thus the cost to design and maintain HoloLens 2-based manufacturing applications. Consequently, this also raises challenges for the standardised development of MR applications in the industry.**

***Keywords*—Mixed Reality, Software architecture, Digital transformation, multimodal interaction, user interface, Operator 4.0**

I. INTRODUCTION

Globalisation and computerisation are two aspects of today's society that add complexity to supply, demand, and global competition. Therefore, this keeps forcing businesses to increase their organisational agility and explore new digital disruptive avenues [1], [2]. The adoption of digital technologies encompassed by Industry 4.0 thus becomes compelling because they promise to address economic factors in the face of growing competition; fast economic development; and demanding productivity performance [3], [4]. This added value is why the US government initiated the Digital Engineering Strategy (DES) [5], and many businesses followed similar steps to shape their practice.

While this demand for new technologies and skills can benefit many businesses, it can also create rapid obsolescence and competitive disadvantage for businesses that resist digital transformation. For example, McKinsey and Company's study predicted a 30% decline in demand for physical and manual skills in manufacturing repeatable and predictable tasks across Europe and the United States. Therefore, companies that fully resist digital transformation can face a 23% downturn [6]. This triggers an emerging problem as the digital transformation itself is becoming unavoidable, and the workforce is not ready for smart manufacturing, nor the artificial intelligence explainability and regulations [7], [8]. Hence, digital transformation can hit a bottleneck where the workforce would operate with 'non-intelligent' yet increasingly complex digital systems.

MR has the potential to offer a ubiquitous digital space that could ease the adoption and implementation of new digital technologies in manufacturing and the capacity-building of digital skills for the workforce [9], [10], [11]. For instance, many studies explore head-mounted MR interfaces that provide immersive data visualisation, off-desk and hands-free interaction, and free mobility in the workspace [10], [11], [12], [13], [14], [15]

Research under the umbrella of Extended Reality (XR) is still in its infancy, with various review papers exploring the potential impact of Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR) on industrial processes. Egger and Masood reviewed 100 publications that explored AR applications for smart manufacturing. 41% of these publications focused on assembly processes and 33% on maintenance processes [14]. Another study analysed 25 publications that researched digital twins, MR, and AR [16]. Almost 60% of them focused on manufacturing topics such as assembly, planning, monitoring, and maintenance. Some studies reported benefits of MR, such as improved visualisation, workflows, and interactions [16]. Regarding manufacturing training, Doolani et al. reviewed the relevant XR publications and highlighted MR benefits for inspection, monitoring, assembly, use of machinery and tools, and cleaning routines in almost every phase of manufacturing [10]. Other authors explored the robotics research XR applications, suggesting visualisation benefits for the interpretation and testing of AI and sensor data [17], [18], [19].

The interest in MR can also be seen in the range of available commercial products that have contributed to research and industrial MR applications. Examples include 2014 MicroOptical's SV-3 [14]; 2017 Microsoft's HoloLens 1 platform [20], [21]; 2019 Microsoft's HoloLens 2 [21], [22]; 2024 Apple Vision Pro [23] or the 2019 Magic Leap device [24]. However, Doolani et al. also highlight that the increasing growth rate of XR hardware and software adds complexity to the consistent design and maintenance of XR applications [10]. For example, while the recent Apple Pro Vision offers better image quality, their research and development communities are not as consolidated as older devices such as Microsoft's HoloLens.

Despite the constant evolution of MR, it is still worth evaluating the current state of the technology's research. On one hand, Merino et al. analysed 458 conference publications for the 2009-2019 period and identified a lack of papers proposing software architecture and evaluating work practices and environment scenarios through ecological validity [25]. Other publications also concluded that laboratory experiments significantly outweigh the use of field experiments [14]. On the other hand, older HoloLens 1 device models appear to dominate the 25-paper systematic literature review of Kunz et al., which focused on AR and Digital Twins [16], and Lu et al. unveil many issues regarding the research of Digital-driven smart manufacturing Digital Twins - including architecture patterns, communication latency requirements, data capture, standards, functionalities, model version management and human roles [26]. Therefore, rushing to experiment with the newest MR devices, more consolidated and capable MR devices would need integration within current functional Cyber-Physical systems (CPS) and Digital twin-based manufacturing ecosystems for ecological validity. In view of the limited availability of resources for the Apple device, and the potential lack of motion sickness of HoloLens' transparent lenses [27], this study will focus on the use of HoloLens technology.

This research aims at integrating the recent HoloLens 2 device (2019) within a Siemens-Festo Cyber-Physical Factory platform's architecture and environment, and it also aims at discussing the resulting integrated architecture, the MR app technical performance aspects, and workflow interactions improvement for the maintenance of such CP Factory.

II. RELATED WORK

A. Cyber-Physical System architecture

Improving maintenance is one of the main manufacturing targets of MR innovations [14], [16]. One main application is predictive maintenance (PdM) or Prognosis and Health Management (PHM), which integrates data, Artificial Intelligence, Internet of Things devices/machines and user interfaces. The foundation for these PdM and PHM systems is a CPS or digital twin architecture that supports the collection, communication and processing of product and equipment data during their manufacturing lifecycle. This concept is also known as Digital Thread which collects the lifecycle's insights and data as feedback for future design stages, as represented in Fig. 1 [28].

Many authors have proposed theoretical and experimental CPS architectures for PdM and PHM [29], [30], [31], [32]. Fig. 2 shows a representative example architecture of a PdM CPS architecture. It includes a digital twin data collection module whose data is used by a machine learning module to form the database. Then, the XR devices visualise to support maintenance decisions. As shown in Fig. 2, this architecture's artificial intelligence units and data analysis units depend on the data collection block.

Although many of the cited architectures were implemented with real manufacturing machines, they mainly consisted of experimental setups or theoretical frameworks that were not integrated into a production system or CPS. Furthermore, they focused on the aspects of artificial intelligence, while the data architecture and data interfaces were not the focus of the evaluation.

Some of these authors also proposed further work on performance criteria, metrics, and adoption considerations [33], data quality [29] and real industrial production unit implementation [32] of the CPS architectures. This opens an opportunity to start exploring the potential of MR and its compatibility with current CPS architectures.

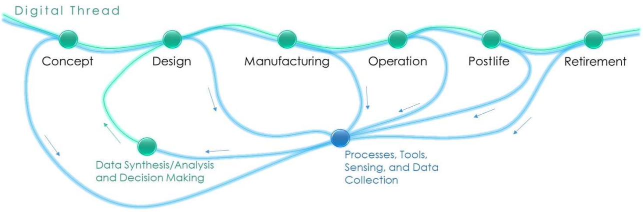


Fig. 1. Digital thread in manufacturing lifecycle management [28]

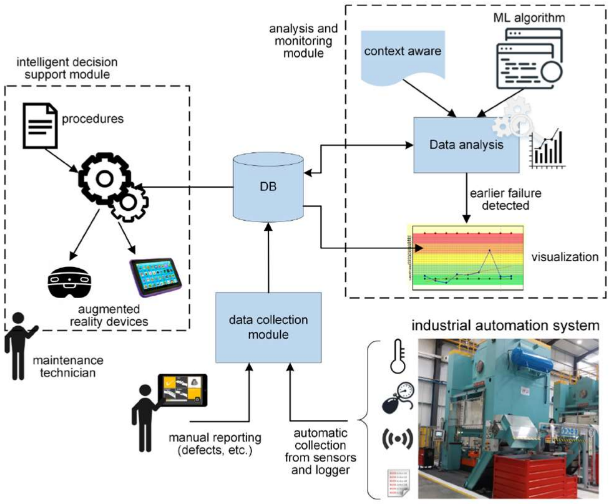


Fig. 2. System architecture for a PdM industrial case study [32]

B. *MR for manufacturing maintenance workflow improvements*

The field of MR has the potential to offer a blend of real and digital features that can support users in a digital environment [9]. This implies a revolutionary interface to interact with manufacturing systems [25], and innovative industrial operator practices [34] that are still under-explored. Many studies explore MR interfaces that provide immersive data visualisation, off-desk and hands-free digital interaction, and free movement within real and digital workspaces [10], [11], [12], [13], [14], [15]. Additionally, many of these MR interactions include multimodal interactions such as hand gestures, voice commands, and eye tracking, among others.

Some studies also supported the idea that combining XR with data management and AI provides even more benefits, for example, better understanding data [44] and designing machine learning models [18], [35]. More examples include digital twin simulation and assistance with chat-bots [36], MR-based structural physical defect detection [37], AR-based robot navigation data visualisation [17], MR-based human-robot collaboration [38] and AR-based assembly instructions support [39], [40].

C. *MR interaction and performance evaluation*

Some fields traditionally combine both qualitative and quantitative methods, namely Human-Computer interaction [41], Human-Centred Design [42]. These disciplines inform the design of digital interfaces and interactions through an in-depth understanding of the users' and/or stakeholders' perspectives, and according to Stephanidis et al., they can be used for MR applications [43]. Furthermore, many of these approaches aim to avoid unnecessary design iterations by taking extra considerations for qualitative studies [13], [25] and some authors argue a need for contextual consideration in interaction design research and field validation [25], [43], [44], [45]. However, these approaches were initially conceived for computers and other flat-screen interfaces. The validation of MR-based CPS software is still emerging, and contributions towards standards will help create consistent and optimised design procedures for an industrial MR body of knowledge.

Alongside usability tests and user experience, many of the technological MR limitations to overcome include but are not limited to, low computing power, machine learning issues, and a narrow field of view (FOV) [9], [10], [14], [16], [46]. Many MR hardware and software providers offer a range of performance tools to evaluate devices, including Windows® Performance Toolkit and Unity performance profiler. However, information on XR devices and software performance is not specified in many research studies. If more research studies disclosed their XR app's performance, the understanding and benchmarking of the XR solutions would be better assisted, especially when software features like video see-through XR's high latency have produced fatigue and motion sickness negative effects [12], [46], [47].

III. METHODOLOGY

For the present study, the methodology has been synthesised in Fig. 3's diagram. The main parts include the architecture components, the MR app workflow and its performance.

A. *Case study: Cyber-Physical Factory, sensor data, communication protocols and HoloLens 2*

The Siemens-Festo Cyber-Physical Factory (CPF) is composed of several manufacturing stations that perform product assembly jobs. Fig. 4 shows two groups of four stations connected by conveyors that simulate drilling, pressing and other assembly tasks to build a simplified phone. The phone is built as it is transported from one station to another via a conveyor or a mobile robot. The stations are controlled by different industrial Siemens PLCs that manage each station's sensors' data and actuators' signals through the OPC-UA protocol and are centralised in a computer [48]. The Github Unity repository from [49] was adapted to create an MR-Unity MQTT server for HoloLens 2 to read data from an MQTT mosquito broker. MQTT was chosen as it is better suited for heavily trafficked networks than OPC-UA, and only one sensor was read.

The setup and programming of the OPC-UA communication infrastructure was already provided by Siemens through a central desktop computer and a collection of different software applications. The NodeRed programming tool [50] was used to retrieve data from one infrared sensor installed in the measuring station's PLCs. This was done by coding an OPC-UA to MQTT gateway in NodeRed that connected to an MQTT broker. Finally, a mosquito broker [51] was installed and configured on the central desktop computer that allowed data flow from the PLC sensor data to the MR-Unity application.

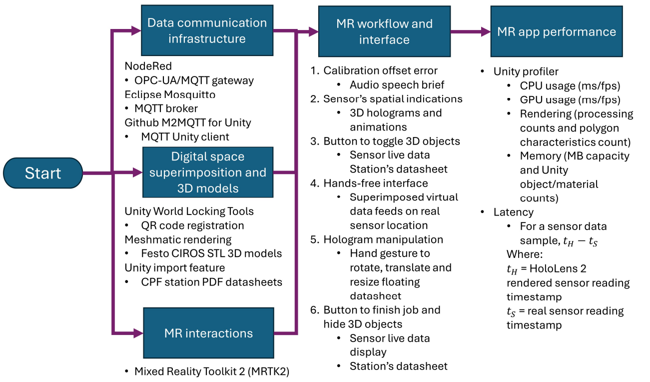


Fig. 3. Methodology diagram including architecture's software functionalities (Left-hand side blocks), interaction workflow (Central block) and performance metrics (Right-hand side block)

Fig. 4. Siemens-Festo CPF case study

B. *Mixed Reality space and interactions authoring*

HoloLens 2 is a very recent platform that provides compatibility with MR authoring tools such as Unity that can interface with industrial communication protocols such as MQTT. Since the present study's scope is to integrate a simple MR application in the CPF system, the specific interaction authoring would not need a rigorous human-centred design methodology. Instead, the interaction aimed at providing distinctive and minimal interactive elements that cannot be achieved through flat screens such as tablets, Human-Machine Interfaces (HMIs) or desktop computers [40].

The premise for the MR functionality was conceived to support a simple calibration task commonly performed by staff to utilise the CPF. This consisted of reading the measuring station's sensor data and adjusting its sensors' height to match the desired offset measurement. The CP Factory's HMI displays normally provide these readings, and the station's PDF datasheet provides extra technical information to support the calibration procedure. Calibrating a sensor's offset value usually requires several interfaces (display, keyboard, mouse, HMIs, and tablet) for completion. For instance, approaching the display or HMIs to check data, holding the tablet, and other tasks can cause the operator to pause the procedure several times. MR then presents an opportunity for hands-free data display within operator's FOV when calibrating the sensor's offset.

Different basic XR building blocks were installed by following the Windows Mixed Reality Toolkit tutorials. For instance, *World Locking Tools for Unity* [52] was implemented to record the CPF space on the HoloLens 2 and allow tracking and space registration. With the help of QR codes, the measuring station hologram was anchored and superimposed on the real measuring station. For this, distance measurements between the real QR code and the measuring station needed to be manually taken. Then, these were modelled in Unity to code the same distance between the virtual QR code and the AutoCAD 3D model of the measuring station.

Regarding multimodal interactions and interactable objects, Microsoft's *HoloLens 2 fundamentals learning path* tutorial [53] was followed to implement many core concepts from the Mixed Reality Toolkit 2 (MRTK2) ranging from interactable buttons, voice commands, floating boxes, orienting arrows, etc. To produce artificial speech, the MRTK2's *MixedRealityToolkit-Unity text-to-speech* class was used.

In terms of holographic design, Siemens provided different STL 3D models and datasheets for the CPF and its sensors. The complete measuring station's physical embodiment and its STL model can be seen in Fig. 5. The 3D models of the supporting structure and sensors were meshed through the Meshmatic software tool [54] to optimise rendering on the MR-Unity app. Siemens-Festo also provided the PDF datasheet and they natively supported imports into Unity.

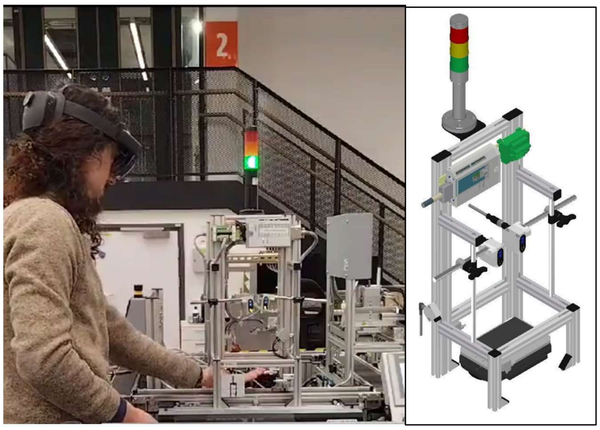


Fig. 5. CPF Measuring station (3D model on the left and real model on the right)

C. *MR-Unity interaction and data visualisation performance*

To evaluate the performance of such devices, benchmarks and other metrics such as latency are often used to compare different technological devices [9], [10]. Microsoft and Unity provide different tools to analyse the performance of the MR application. Available performance tools include the Windows Device Portal 'Performance Tracing' page for Microsoft HoloLens 2 [55]; the in-application MRTK2 performance Visual profiler [56]; the Unity profiler [57]; and the Windows Performance Toolkit Recorder & Analyzer (WPR & WPA) [58]. All the previous tools can be used to evaluate the performance of HoloLens 2. These tools allow developers to log, record, and analyse different performance metrics. However, no Microsoft's or Unity's MR performance optimisation tutorials were followed.

The targeted performance data include CPU usage to evaluate the frame per second; GPU usage; memory; rendering counts, Garbage Collector (GC) usage, etc. These will help to understand how the HoloLens 2 performs within the CPF architecture while displaying data from one sensor arriving from the MQTT communication protocol.

The Unity profiler will be used in this study to evaluate the MR-Unity app's performance. Although Windows® Performance Toolkit [58] produces more in-depth performance profiles, it is not optimised for Unity apps and does not show information such as the 'frames per second' rate.

The sensor signal readings experience a series of delays until they are displayed on the MR Unity app. This usually happens when the signal is exchanged between the CPS elements [59]. For the proposed architecture the infrared sensor signal is interfered with a PLC, the OPC-UA/MQTT gateway, the MQTT broker, the Unity MQTT client and finally the MR Unity hologram display. This introduces latency and negatively affects real-time metrics. For this reason, the latency metric will also be monitored to assess the performance of the real-time data visualisation. The method of calculation can be done by recording a step change timestamp of the sensor readings and the step change timestamp when the updated value is observed in the Unity MR app. The Siemens-Festo CPF can provide the timestamp when the signal is intercepted by the MQTT gateway and MQTT client. However, it was not possible to extract the timestamp when producing the step change and when observing the step change on the HoloLens 2. Hence, the time difference had to be manually obtained by a timer. The results would be indicative of this metric while the proper timestamp collection method is developed. 30 timestamps were collected to produce 15 latency readings, and the latter values were averaged to obtain an indicative value.

IV. RESULTS: MR+FACTORY SYSTEM ARCHITECTURE AND MR INTERACTION

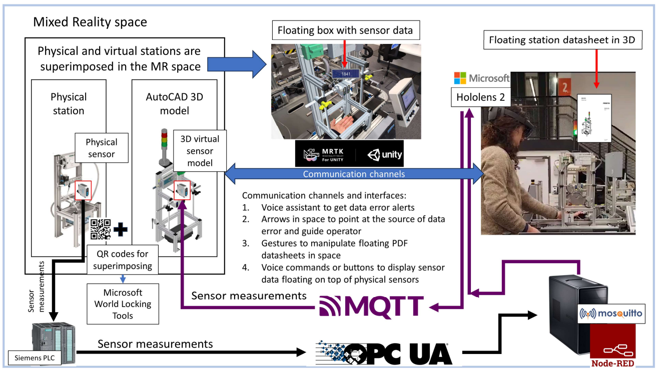
A. *MR-based Siemens-Festo CPF architecture*

The implemented architecture includes three main parts: The data communication infrastructure, the MR interactions, and the registration/superimposition of the digital space on the real. The integration of all these parts can be seen in Fig. 6.

From left to right, this resulting architecture included a communication system that managed the data produced by one sensor installed at the CP Factory physical measuring station. It travelled to the main computer via OPC-UA where a NodeRed flow code bridged the OPC-UA sensor readings to MQTT and deposited them on a mosquito MQTT broker. The HoloLens 2's MQTT client read the sensor readings from the broker, rendered them and displayed them on the 3D hologram model of the measuring station. To support this functionality, the HoloLens 2 MR interactions were designed to guide the user to identify the location of the sensor in space and visualise its data and the complete station's rendered datasheet.

B. *MR-based manufacturing workflow and interface*

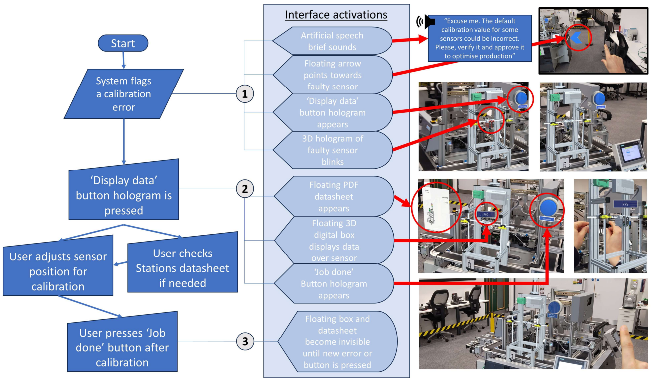
As shown in Fig. 7, the interaction started with an artificial speech audio that flagged an error and summarised the need to calibrate the sensor offset values. Then, the MR interface provided a holographic arrow that pointed at the measuring station as denoted by the first two interface activations. This arrow floated at the centre of the HoloLens 2 user's FOV and followed the head movement until the station was in the user's FOV. At this point, the virtual sensor 3D model blinked with red tones to catch the user's attention. The user would then press the button to display the sensor data above the real sensor and a datasheet document floating on the side. At this stage, the user would perform the calibration of the system by twisting a knob and adjusting the height of the sensor to get the desired offset measurement. Once finished, the user would press the button 'Job done' to hide the sensor data and datasheet.



Communication channels and interfaces:

1. Voice assistant to get data error alerts
2. Arrows in space to point at the source of data error and guide operator
3. Gestures to manipulate floating PDF datasheets in space
4. Voice commands or buttons to display sensor data floating on top of physical sensors

Fig. 6. MR-based sensor calibration interface for the Siemens-Festo CPF



"Excuse me. The default calibration value for some sensors could be incorrect. Please, verify it and approve it to optimise production"

Fig. 7. MR-Unity app interaction workflow and interface features

C. *Unity profiler performance results*

Fig. 8 shows the Unity profiler performance readings (Labelled and unlabelled) for the entire MR-Unity app workflow time. Yellow vertical lines were added to represent the timestamps between each action, and each action was depicted by a white box. From left to right, the actions include:

- The user is away from the station when the 'floating arrow' appears.
- The user will be 'looking at the station' after following the floating arrow with their gaze.
- The user approaches the station to be 'near the station'.
- The user performs a tapping hand gesture for the 'display button to be pressed'
- The user performs the 'sensor offset calibration' job.
- The user 'manipulates the floating PDF datasheet' with hand gestures to change its 3D positioning and size in space.
- The user will move near the 'Job done' button to press it.

Throughout the entire workflow, we can observe that the CPU usage mostly remains at 60 fps in Fig. 8. However, it had several peaks that reached 33ms or even 66ms processing time which reduces fps to 30 fps or 15 fps respectively. Most of the fps peaks were approximately at 30fps, and they were a total of 48. The peak period is mostly 438.3ms and it almost doubled during the calibration job. This highlights the limitations of 3D model optimisation tools such as Meshmatic, and the need for MR app-specific performance optimisation. App-specific optimisation can include, but is not limited to, the analysis of performance bottlenecks and Microsoft's MR debugging recommendations.

Regarding the GPU usage, the performance data did not show any significant changes, except for the manipulation of the PDF datasheet 3D model. Similarly to the CPU results, the Unity import feature can have limited rendering of the datasheet and it will need manual optimisation. Moreover, the experienced visualisation and manipulation of the datasheet had significant jitter which can also mean desync issues between left and right lenses.

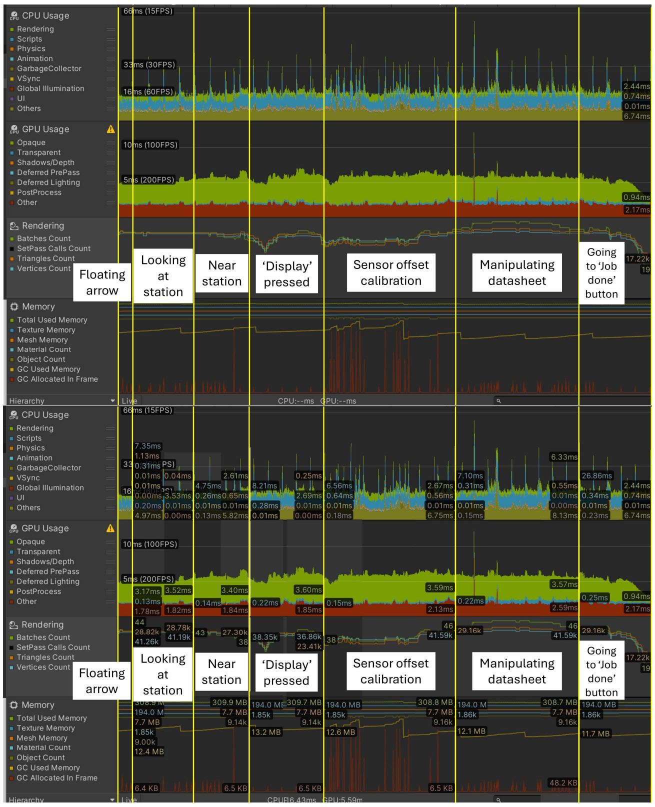


Fig. 8. Unity profiler performance data (Unlabelled data above and labelled data below) The white boxes represent the actions taken between the yellow timestamps.

Rendering depended on the number of polygons and meshed structures that the MR-Unity had to display on the HoloLens 2. It makes sense that if only one button is within the FOV, the count will be reduced. However, although the PDF datasheet import was supported by Unity, the rendering was not optimised for performance. This means that extra rendering is needed for PDF files.

The memory figures present higher utilisation of the GC during the 'Sensor offset calibration. According to Microsoft's documentation, GC is activated to automatically release memory for an application. Then, according to Microsoft's *Fundamentals of Garbage Collection*, this usually means that the system has low physical memory, or the memory has surpassed an acceptable threshold. If we consider that the MQTT data was also received – but not displayed – before the calibration job; this suggests that live data bandwidth and holographic data display updates would also need further optimisation for MR.

Finally, the MR-Unity experience had a noticeable latency but an indicative value in the order of hundreds of milliseconds or approximately 500ms was taken. The PLC's sensor data readings were definitely not displayed in real-time on the MR-Unity HoloLens 2 experience. Although the calibration was performed by waiting for stable values, this lag can have a high impact on maintenance tasks leading to job delays or human errors. An in-depth software optimisation process will be required including hologram complexity (e.g., minimalist models) and communication protocol complexity (e.g., OPC-UA client instead of MQTT gateway)

V. DISCUSSION OF THE RESULTS

A. *MR-based CPF maintenance architecture*

The implemented architecture provides an MR interface that can perform a simple offset calibration task of manufacturing sensors within a manufacturing system. This opens a door to interface MR with Siemens-Festo industrial hardware products such as the CPF which includes PLC, HMIs, and Internet of Things (IoT) devices arranged in an assembly line fashion. Likewise, this architecture supports further development of MR design guidelines for recent Digital Twin ISO standards such as 'ISO/AWI 23247 - Digital Twin manufacturing framework' [60]. This and more case study-based architectures can also enhance experimental setups by enriching their contextual value and ecological validity [13], [25]. However, while the presented architecture effectively integrated MR, CPS, and IoT technologies, scalability considerations could significantly affect performance and feasibility [26].

The implemented architecture did not interface with Siemens software products such as Siemens Insights Hub which includes data analytics tools [61]. However, future work can integrate the Siemens Insights Hub's MQTT broker and MQTT certificates to access data analytics, cybersecurity and production planning functions. Furthermore, it is important to link the architecture to PdM and maintenance scheduling functionalities to start exploring the technical and architectural feasibility of artificial intelligence features and support the emerging trends [62]. For instance, Siemens AI lab or Microsoft's Azure should be explored to evaluate their fitness for PdM capabilities

B. *MR interaction advantages over flat interfaces*

The interactions designed offered two unique advantages against flat screen interfaces such as tablets, HMIs and desktop computers. First, the floating arrow's visual guidance supported the experimenter's job by explicitly indicating the faulty sensor's location in space. This advantage can contribute to better situational awareness and less stress which is beneficial for the user as suggested in Korner et al.'s study [63]. Then, hands-free sensor readings within the user's FOV avoided the effects of the 'divided-attention paradigm' [13] when manually adjusting the height of the sensor. This means that the user did not have to turn their heads or body or use their hands repeatedly to check the sensor readings during the calibration job. However, HoloLens 2 can still cause fatigue due to 'focal rivalry' and 'vergence-accommodation' eye phenomena [47].

Although the previous advantages may be resolving common user experience issues, the evidence is limited to some discussions with the local staff that worked with the CPF with no feedback to validate the benefits. It would be recommended to apply specific HCI or HCD systematic methods for design and evaluation that consider the users. Examples include, but are not limited to, questionnaires, interviews, focus groups, observation of participants in their context of work, and experiments. [41], [42]. However, the immaturity of the MR technology can hinder the systematic evaluation of MR functionalities and their associated user experience resulting in a ‘chicken and egg’ situation [1], [4], [9]. As the MR technology matures, an alternative avenue to evaluate user experience and performance is conducting ‘Wizard of Oz’ studies where enacted artificial intelligence immerses users in an MR scenario [64].

C. Performance and quality of the MR app interactions

The MR-Unity app performance results indicate that not only the architecture and data exchange need to be optimised, but also the hologram models. This raises many concerns for real-world implementation via the HoloLens 2 device.

First, it is necessary to question the HoloLens 2 device’s implementation requirements and associated costs within a manufacturing context and ecosystem. The results reveal that a Meshmatic optimisation of Siemens STL file is not enough. Likewise, importing PDF to Unity caused later performance issues during the MR Unity experience. Hence, the models’ meshes should be redesigned to reduce the hologram density. However, this will be highly dependent on the 3D model, and it may need specific tailoring. Therefore, if further optimisation work is needed, this may eventually increase the cost and dependence on an expert software engineer or external service to tailor and maintain deployed MR-Unity applications. While this could deter companies from using MR applications in the processes, emergent ChatGPT functionalities are starting to automate Unity script development [65]. This can eventually accelerate these processes and reduce costs affecting return on investments.

In terms of data exchange the main concern is scalability. The current architecture uses one sensor which significantly affects the device’s performance and real-time visualisation when its data is displayed. The performance data shows that the ideal 60fps is not stable for CPU Usage, and the data display has a latency in the order of hundreds of milliseconds. Further work should evaluate the performance of the MR-Unity app with different numbers of sensor data streams, and hologram densities. For example, the application of the proposed Quality of Service aspects for digital twins [59], or other ISO guidelines such as ISO 23247-1:2021 [60], could be followed to define the HoloLens 2’s authoring requirements when used with Siemens-Festo hardware and OPC-UA/MQTT gateways.

Some further limitations of this study include the precision of the Unity profiler data and the latency calculations. Although that profiler data provides different insights, it is meant to identify performance changes to evaluate script changes and not specific values for the overall MR-Unity performance. Moreover, the MR-Unity app’s entire workflow will benefit from a thorough performance analysis in accordance with other quality benchmark guidelines or tools such as Windows Performance Toolkit Recorder & Analyzer (WPR & WPA) [58]. Latency will need to be explored further as this metric can be also affected by the ageing of CPS and sensors, the HoloLens 2 battery state, manufacturing differences and scalability factors.

VI. CONCLUSION

MR offers unique spatial interactions that can further enhance manufacturing workers' performance alongside the accelerated adoption of digital skills and emerging artificial intelligence tools. The present study extends the literature by implementing and evaluating the Siemens-Festo CPF with the HoloLens 2 MR device. The results confirm that MR devices and industrial CPS can be integrated but a significant amount of tailoring and optimisation is needed for a smooth and real-time experience. This implementation can serve as a foundation to explore other MR devices and industrial CPS; MR head-mounted interactions that outperform flat screens; and MR-Unity performance benchmarking tools to evaluate MR applications. These benefits would ultimately help to build standards that encompass MR, CPS and digital twin systems implementation in manufacturing contexts.

The main concerns in this study prioritise a repeatable, consistent procedure to mass produce MR apps for manufacturing. The following recommendations set the ground for future research work towards solving this concern:

- Rendering optimisation procedures for hologram models
- Latency impact factors that can amount to large signal delays
- Communication protocol optimisation procedure for MR-CPS applications (Including data bandwidth and display holograms)
- MR-Unity app user validation through Human-computer interaction methods
- Benchmarking standardisation for MR-Unity apps’ performance
- Terminology for distinctive MR interactive features that can differentiate MR from flat screens.

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REFERENCES

[1] M. Ghobakhloo, M. Fathi, M. Iranmanesh, P. Maroufkhani, and M. E. Morales, “Industry 4.0 ten years on: A bibliometric and systematic review of concepts, sustainability value drivers, and success determinants,” J Clean Prod, vol. 302, p. 127052, Jun. 2021, doi: 10.1016/J.JCLEPRO.2021.127052.

[2] S. Kraus, P. Jones, N. Kailer, A. Weinmann, N. Chaparro-Banegas, and N. Roig-Tierno, “Digital Transformation: An Overview of the Current State of the Art of Research,” Sage Open, vol. 11, no. 3, Sep. 2021, doi: https://doi.org/10.1177/21582440211047576.

[3] M. Ghobakhloo, “Industry 4.0, digitization, and opportunities for sustainability,” J Clean Prod, vol. 252, p. 119869, Apr. 2020, doi: 10.1016/J.JCLEPRO.2019.119869.

[4] D. Horváth and R. Z. Szabó, “Driving forces and barriers of Industry 4.0: Do multinational and small and medium-sized companies have equal opportunities?,” Technol Forecast Soc Change, vol. 146, pp. 119–132, Sep. 2019, doi: 10.1016/J.TECHFORE.2019.05.021.

[5] K. Baldwin, J. Stanley, R. H. Kewley Jr., and W. Bray, “Department of Defense - Digital Engineering Strategy,” Washington, D.C., Jun. 2018.

[6] E. de Boer, K. Ellingrud, G. Richter, and D. Swan, “What are Industry 4.0, the Fourth Industrial Revolution, and 4IR?,” Aug. 2022.

[7] F. M. Zanzotto, “Viewpoint: Human-in-the-loop artificial intelligence,” Journal of Artificial Intelligence Research, vol. 64, pp. 243–252, Feb. 2019, doi: 10.1613/jair.1.11345.

[8] Y. Lu, “Artificial intelligence: a survey on evolution, models, applications and future trends,” Journal of Management Analytics, vol. 6, no. 1, pp. 1–29, Jan. 2019, doi: 10.1080/23270012.2019.1570365.

[9] S. Rokhsaritalemi, A. Sadeghi-Niaraki, and S. M. Choi, “A review on mixed reality: Current trends, challenges and prospects,” Applied Sciences, vol. 10, no. 2, p. 636, Jan. 2020, doi: 10.3390/app10020636.

[10] S. Doolani et al., “A Review of Extended Reality (XR) Technologies for Manufacturing Training,” Technologies (Basel), vol. 8, no. 4, p. 77, Dec. 2020, doi: 10.3390/technologies8040077.

[11] A. Rasheed, O. San, and T. Kvamsdal, “Digital twin: Values, challenges and enablers from a modeling perspective,” IEEE Access, vol. 8, pp. 21980–22012, 2020, doi: 10.1109/ACCESS.2020.2970143.

[12] S. H.-W. Chuah, “Why and Who Will Adopt Extended Reality Technology? Literature Review, Synthesis, and Future Research Agenda,” SSRN research repository. Elsevier BV, Jan. 09, 2019. doi: 10.2139/ssrn.3300469.

[13] D. Szafir, “Mediating Human-Robot Interactions with Virtual, Augmented, and Mixed Reality,” in International Conference on Human-Computer Interaction (HCII): Virtual, Augmented and Mixed Reality. Applications and Case Studies (VAMR), Springer Verlag, Jul. 2019, pp. 124–149. doi: 10.1007/978-3-030-21565-1_9.

[14] J. Egger and T. Masood, “Augmented reality in support of intelligent manufacturing – A systematic literature review,” Comput Ind Eng, vol. 140, p. 106195, Feb. 2020, doi: 10.1016/J.CIE.2019.106195.

[15] W. Fang, T. Zhang, L. Chen, and H. Hu, “A survey on HoloLens AR in support of human-centric intelligent manufacturing,” Journal of Intelligent Manufacturing 2023, pp. 1–25, Nov. 2023, doi: 10.1007/S10845-023-02247-5.

[16] A. Kunz, S. Rosmann, E. Loria, and J. Pirker, “The Potential of Augmented Reality for Digital Twins: A Literature Review,” in IEEE Conference on Virtual Reality and 3D User Interfaces (VR), Institute of Electrical and Electronics Engineers Inc., 2022, pp. 389–398. doi: 10.1109/VR51125.2022.00058.

[17] L. Kastner and J. Lambrecht, “Augmented-Reality-Based Visualization of Navigation Data of Mobile Robots on the Microsoft Hololens - Possibilities and Limitations,” in IEEE International Conference on Cybernetics and Intelligent Systems (CIS) and IEEE Conference on Robotics, Automation and Mechatronics (RAM), Institute of Electrical and Electronics Engineers Inc., Nov. 2019, pp. 344–349. doi: 10.1109/CIS-RAM47153.2019.9095836.

[18] D. Szafir and D. A. Szafir, “Connecting human-robot interaction and data visualization,” in ACM/IEEE International Conference on Human-Robot Interaction, IEEE Computer Society, Mar. 2021, pp. 281–292. doi: 10.1145/3434073.3444683.

[19] A. Zea and U. D. Hanebeck, “iviz: A ROS visualization app for mobile devices,” Software Impacts, vol. 8, p. 100057, May 2021, doi: 10.1016/j.simpa.2021.100057.

[20] R. Hammady, “Virtual Guidance using Mixed Reality in Historical Places and Museums MuseumEye-a HoloLens-based Mixed Reality Guide to the Egyptian Museum in Cairo,” Staffordshire University, Staffordshire, 2019.

[21] S. Park, S. Bokijonov, and Y. Choi, “Review of Microsoft HoloLens Applications over the Past Five Years,” Applied Sciences, vol. 11, no. 16, p. 7259, Aug. 2021, doi: 10.3390/APP11167259.

[22] I. Soares, R. B. Sousa, M. Petry, and A. P. Moreira, “Accuracy and Repeatability Tests on HoloLens 2 and HTC Vive,” Multimodal Technologies and Interaction, vol. 5, no. 8, p. 47, Aug. 2021, doi: 10.3390/MTI5080047.

[23] R. Cheng, N. Wu, M. Varvello, E. Chai, S. Chen, and B. Han, “A First Look at Immersive Telepresence on Apple Vision Pro,” Proceedings of ACM Conference (Conference’17), vol. 1, May 2024, Accessed: Jun. 21, 2024. [Online]. Available: https://arxiv.org/abs/2405.10422v1

[24] Z. M. Achmad et al., “Integration Mixed Reality with Internet of Things by Using Magic Leap,” International Conference on Electrical Engineering, Computer Science and Informatics (EECSI), pp. 661–666, 2023, doi: 10.1109/EECSI59885.2023.10295629.

[25] L. Merino, M. Schwarzl, M. Kraus, M. Sedlmair, D. Schmalstieg, and D. Weiskopf, “Evaluating Mixed and Augmented Reality: A Systematic Literature Review (2009-2019),” in International Symposium on Mixed and Augmented Reality (ISMAR), Institute of Electrical and Electronics Engineers Inc., Nov. 2020, pp. 438–451. doi: 10.1109/ISMAR50242.2020.00069.

[26] Y. Lu, C. Liu, K. I. K. Wang, H. Huang, and X. Xu, “Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues,” Robot Comput Integr Manuf, vol. 61, p. 101837, Feb. 2020, doi: 10.1016/J.RCIM.2019.101837.

[27] M. Drouot, N. Le Bigot, J. Bolloc’h, E. Bricard, J. L. de Bougrenet, and V. Nourrit, “The visual impact of augmented reality during an assembly task,” Displays, vol. 66, p. 101987, Jan. 2021, doi: 10.1016/J.DISPLA.2021.101987.

[28] V. Singh and K. E. Willcox, “Engineering Design with Digital Thread,” https://doi.org/10.2514/1.J057255, vol. 56, no. 11, pp. 4515–4528, Sep. 2018, doi: 10.2514/1.J057255.

[29] J. Lee, J. Ni, J. Singh, B. Jiang, M. Azamfar, and J. Feng, “Intelligent Maintenance Systems and Predictive Manufacturing,” Journal of Manufacturing Science and Engineering, Transactions of the ASME, vol. 142, no. 11, Nov. 2020, doi: 10.1115/1.4047856/1085488.

[30] F. Calabrese, A. Regattieri, M. Bortolini, M. Gamberi, and F. Pilati, “Predictive Maintenance: A Novel Framework for a Data-Driven, Semi-Supervised, and Partially Online Prognostic Health Management Application in Industries,” Applied Sciences 2021, Vol. 11, Page 3380, vol. 11, no. 8, p. 3380, Apr. 2021, doi: 10.3390/APP11083380.

[31] C. Cimini, F. Pirola, R. Pinto, and S. Cavalieri, “A human-in-the-loop manufacturing control architecture for the next generation of production systems,” J Manuf Syst, vol. 54, pp. 258–271, Jan. 2020, doi: 10.1016/J.JMSY.2020.01.002.

[32] F. Alves et al., “Deployment of a Smart and Predictive Maintenance System in an Industrial Case Study,” IEEE International Symposium on Industrial Electronics, vol. 2020-June, pp. 493–498, Jun. 2020, doi: 10.1109/ISIE45063.2020.9152441.

[33] C. Emmanouilidis et al., “Enabling the human in the loop: Linked data and knowledge in industrial cyber-physical systems,” Annu Rev Control, vol. 47, pp. 249–265, Jan. 2019, doi: 10.1016/j.arcontrol.2019.03.004.

[34] D. Romero, J. Stahre, and M. Taisch, “The Operator 4.0: Towards socially sustainable factories of the future,” Comput Ind Eng, vol. 139, p. 106128, Jan. 2020, doi: 10.1016/J.CIE.2019.106128.

[35] A. Chatzimparmpas, R. M. Martins, I. Jusufi, and A. Kerren, “A survey of surveys on the use of visualization for interpreting machine learning models,” Inf Vis, vol. 19, no. 3, pp. 207–233, Mar. 2020, doi: 10.1177/1473871620904671.

[36] A. A. Malik, T. Masood, and A. Bilberg, “Virtual reality in manufacturing: immersive and collaborative artificial-reality in design of human-robot workspace,” International Journal of Computer Integrated Manufacturing, vol. 33, no. 1, pp. 22–37, Jan. 2019, doi: 10.1080/0951192X.2019.1690685.

[37] E. Karaaslan, U. Bagci, and F. N. Catbas, “Artificial Intelligence Assisted Infrastructure Assessment using Mixed Reality Systems,” Transportation Research Record: Journal of the Transportation Research Board., vol. 2673, no. 12, pp. 413–424, Jul. 2019, doi: 10.1177/0361198119839988.

[38] L. El Hafi et al., “System for augmented human–robot interaction through mixed reality and robot training by non-experts in customer service environments,” Advanced Robotics, vol. 34, no. 3–4, pp. 157–172, Feb. 2019, doi: 10.1080/01691864.2019.1694068.

[39] Z. H. Lai, W. Tao, M. C. Leu, and Z. Yin, “Smart augmented reality instructional system for mechanical assembly towards worker-centered intelligent manufacturing,” J Manuf Syst, vol. 55, pp. 69–81, Apr. 2020, doi: 10.1016/J.JMSY.2020.02.010.

[40] E. Laviola, M. Gattullo, V. M. Manghisi, M. Fiorentino, and A. E. Uva, “Minimal AR: visual asset optimization for the authoring of augmented reality work instructions in manufacturing,” International Journal of Advanced Manufacturing Technology, vol. 119, no. 3–4, pp. 1769–1784, Mar. 2022, doi: 10.1007/S00170-021-08449-6/FIGURES/8.

[41] P. Cairns and A. Cox, Research methods for human-computer interaction., 1st ed., vol. 10. Cambridge: Cambridge University Press, 2008. Accessed: Aug. 11, 2022. [Online]. Available: https://psycnet.apa.org/record/2008-14833-000

[42] H. Nguyen Ngoc, G. Lasa, and I. Iriarte, "Human-centred design in industry 4.0: case study review and opportunities for future research," J Intell Manuf, pp. 1–42, Jun. 2021, doi: 10.1007/S10845-021-01796-X.

[43] C. Stephanidis et al., "Seven HCI Grand Challenges," Int J Hum Comput Interact, vol. 35, no. 14, pp. 1229–1269, Aug. 2019, doi: 10.1080/10447318.2019.1619259.

[44] N. Kumar and S. C. Lee, "Human-machine interface in smart factory: A systematic literature review," Technol Forecast Soc Change, vol. 174, p. 121284, Jan. 2022, doi: 10.1016/J.TECHFORE.2021.121284.

[45] G. Aceto, V. Persico, and A. Pescapé, "A Survey on Information and Communication Technologies for Industry 4.0: State-of-the-Art, Taxonomies, Perspectives, and Challenges," IEEE Communications Surveys and Tutorials, vol. 21, no. 4, pp. 3467–3501, Oct. 2019, doi: 10.1109/COMST.2019.2938259.

[46] M. Eswaran and M. V. A. R. Bahubalendruni, "Challenges and opportunities on AR/VR technologies for manufacturing systems in the context of industry 4.0: A state of the art review," J Manuf Syst, vol. 65, pp. 260–278, Oct. 2022, doi: 10.1016/J.JMSY.2022.09.016.

[47] T. Williams, L. Hirshfield, N. Tran, T. Grant, and N. Woodward, "Using augmented reality to better study human-robot interaction," in Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), Springer, 2020, pp. 643–654. doi: 10.1007/978-3-030-49695-1_43.

[48] "CP Factory / Lab - Festo Didactic InfoPortal," Festo - didactic. [Online]. Available: https://ip.festo-didactic.com/InfoPortal/CPFactoryLab/overview/index.php?lang=en

[49] "GitHub - gpvigano/M2MqttUnity: M2MQTT for Unity." Accessed: Jun. 03, 2024. [Online]. Available: https://github.com/gpvigano/M2MqttUnity

[50] "Node-RED." Accessed: Jun. 03, 2024. [Online]. Available: https://nodered.org/

[51] "Eclipse Mosquitto." Accessed: Jun. 03, 2024. [Online]. Available: https://mosquitto.org/

[52] "World Locking Tools documentation | Microsoft Learn." Accessed: Jun. 03, 2024. [Online]. Available: https://learn.microsoft.com/en-us/mixed-reality/world-locking-tools/

[53] "HoloLens 2 fundamentals: develop mixed reality applications - Training | Microsoft Learn." Accessed: Jun. 03, 2024. [Online]. Available: https://learn.microsoft.com/en-us/training/paths/beginner-hololens-2-tutorials/

[54] "Meshmatic CAD conversion and optimization." Accessed: Jun. 03, 2024. [Online]. Available: https://meshmatic3d.com/

[55] "Using the Windows Device Portal - Mixed Reality | Microsoft Learn." Accessed: Jun. 03, 2024. [Online]. Available: https://learn.microsoft.com/en-us/windows/mixed-reality/develop/advanced-concepts/using-the-windows-device-portal

[56] "Using the visual profiler - MRTK 2 | Microsoft Learn." Accessed: Jun. 03, 2024. [Online]. Available: https://learn.microsoft.com/en-us/windows/mixed-reality/mrtk-unity/mrtk2/features/diagnostics/using-visual-profiler?view=mrtkunity-2022-05

[57] "Unity - Manual: Profiler overview." Accessed: Jun. 03, 2024. [Online]. Available: https://docs.unity3d.com/Manual/Profiler.html

[58] "Windows Performance Toolkit | Microsoft Learn." Accessed: Jun. 03, 2024. [Online]. Available: https://learn.microsoft.com/en-us/windows-hardware/test/wpt/

[59] L. Rauchhaupt et al., "Network-based Communication for Industrie 4.0– Proposal for an Administration Shell," 2016. Accessed: Jun. 03, 2024. [Online]. Available: https://www.plattform-i40.de/IP/Redaktion/EN/Downloads/Publikation/network-based-communication-for-i40-it-summit.html

[60] "ISO 23247-1:2021 - Automation systems and integration — Digital twin framework for manufacturing — Part 1: Overview and general principles," 2021. Accessed: Jun. 03, 2024. [Online]. Available: https://www.iso.org/standard/75066.html

[61] "Insights Hub | Siemens Software." Accessed: Jun. 03, 2024. [Online]. Available: https://plm.sw.siemens.com/en-US/insights-hub/

[62] A. Ucar, M. Karakose, and N. Kırımça, "Artificial Intelligence for Predictive Maintenance Applications: Key Components, Trustworthiness, and Future Trends," Applied Sciences 2024, Vol. 14, Page 898, vol. 14, no. 2, p. 898, Jan. 2024, doi: 10.3390/APP14020898.

[63] U. Körner, K. Müller-Thur, T. Lunau, N. Dragano, P. Angerer, and A. Buchner, "Perceived stress in human–machine interaction in modern manufacturing environments—Results of a qualitative interview study," Stress and Health, vol. 35, no. 2, pp. 187–199, Apr. 2019, doi: 10.1002/SMI.2853.

[64] L. D. RiekLaurel, "Wizard of Oz studies in HRI," J Hum Robot Interact, pp. 119–136, Jul. 2012, doi: 10.5898/JHRI.1.1.RIEK.

[65] J. Huang and K. Huang, "ChatGPT in Gaming Industry," pp. 243–269, 2023, doi: 10.1007/978-3-031-45282-6_9.