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XAI Sustainable Human in the Loop Maintenance

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Abstract: The field of Explainable Artificial Intelligence (XAI) is a relatively new approach to AI, with the aim to provide black box algorithms with human intelligible narrative functionality. It is most often in end-of-life considerations of the asset lifecycle that sustainability issues are encountered. Modern maintenance practice requires a holistic understanding of lifecycle and options for sustainable asset treatments. human in the loop solutions offer a way to leverage both machine and human skill sets to provide the next level of automaton solutions for industrial maintenance activities. This paper presents a framework for human in the loop Intelligent and Sustainable Maintenance. In bridging the gap between machines and humans XAI leverages the best of both worlds to provide a new level of agility to cyber assisted maintenance activities and full lifecycle consideration of assets; a notion that is necessary throughout the organization in the achievement of sustainability goals set by governments around the world in the achievement of a net zero carbon emission economy.

Keywords: Human in the loop; Intelligent maintenance systems; Industry 5.0; Predictive maintenance; Operator 5.0

1. INTRODUCTION

The field of Explainable Artificial Intelligence (XAI) is a relatively new contribution in the Artificial Intelligence (AI) Arena. XAI has the aim of providing AI algorithms with narrative functionality; capable of communicating the major steps taken in arriving at a solution, to a human. With many algorithms exhibiting complexity, while often implemented in a black box format, there is often still a need to include human decision making in the operation of even the most sophisticated industrial automation solutions. Maintenance practice is one such area that is dependent on human skills and experience in the execution of most tasks. Adadi and Berrada, (2018) define four reasons for XAI narratives: Explanations that justify a decision or action; Explanations for control situations; Explanations to improve a process or activity; Explanations to aid discovery. The notion of human-machine dialogue, where humans are able to further question explanations and 'converse' with XAI equipped assets, is an important one; Adadi and Berrada, (2018) conclude in this direction that the power of XAI is in its potential to support AI generated decisions. In envisioning the development of new maintenance automation systems, it is arguable that the empowerment of the human should be a core aim in order to realize both productivity and reliability of maintained assets. While there has been an active move towards the adoption of Industry 4.0 automation technology in the maintenance sector this has sometimes led to a dilution or neglect of the human capacity for problem solving. The recognition of workers and the roles they can still perform in the modern manufacturing organization has led to the proposal of Industry 5.0, putting forward, as a major research strand, the notion of human centric technology for shop floor and supervisory roles (Breque et al. 2021). In Nahavandi (2019) the point is made that Industry 5.0 will, in many cases, require enhanced human-machine interactivity; in the discussion of Cobots (Collaborative Robots). This paper presents a framework for human in the loop Intelligent and Sustainable Maintenance as a response to this need.

2. APPLIED USES FOR XAI

Turner et al. (2021) along with Nahavandi (2019) make the case for use of XAI (Explainable Artificial Intelligence) techniques with Cobots, allowing such robots to communicate and present future activities in the form of human intelligible narratives. The medical sector has been an active area for XAI application and research. In a survey by Tjoa et al. (2021) the use of Deep Learning techniques in medical diagnosis in combination with XAI is explored; finding that explainable techniques are capable of increasing confidence in the results provided by such Blackbox operation algorithms, by providing reasoning for the judgements made. XAI's application has also been investigated for predictive maintenance by Hrnjica and Softic (2020). The assessed papers show the burgeoning

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multidisciplinary area of research that is XAI, thus validating the conclusion that XAI-based methods are gaining popularity, due to lack of trust in existing ML-based systems (Hanif et al., 2021).

3. HUMAN IN THE LOOP AND SUSTAINABLE MAINTENANCE

The need for and practical implementations scoping how the human interacts with automation systems is an ongoing debate, with human in the loop proponents arguing for an overarching need for mediation and decision-making role within a cyber physical system framework (Turner et al. 2021; Nunes et al. 2015). In the field of safety critical control systems there is a need for occasional human interventions, presenting a challenge to the design of assets that require both autonomous and human direction (Li, et al. 2014). It is arguable that this challenge posed by a space shared by both intelligent automation systems and the human operator poses issues related to trust and communication between the two entries. In such scenarios scope exists for XAI technologies to provide confidence building explanatory narratives to the human for discrete instances where decisions require referral and/or part of a process is still required to be undertaken manually. Such generated narratives must, by nature, require a fusion of multiple data points in their construction with requisite complexity.

of Epistemic curiosity may provide a research direction in the further development of frameworks to gauge the relevance and likely acceptance of the generated explanation. Emmanouilidis et al. (2019) make the case for the use of semantic descriptions to identify and highlight to the worker linkages between data and knowledge. Context awareness is key in the use and further development of XAI (Adadi and Berrada, 2018) and semantic technologies do provide a structure for the communication and further processing of the requisite narratives (Turner, et al. 2021).

It is in the end-of-life considerations of the asset lifecycle that sustainability issues are most often encountered, when considering the maintenance of fixed plant and machines of a manufacturing shop floor. The circular economy provides a wider context and outline framework for sustainability considerations for manufactured products in a move away from the current 'take, make, dispose' model of production (Morlet et al., 2016). The rise of the Internet of Things (IoT) has led to greater interoperability between physical assets and distributed digital information systems. It could even be argued that many modern production machine and complex manufactured products could also be described as 'intelligent' in the amount and sophistication of 'on-board' digital processing that they provide. Meyer et al. (2009) underline the importance of defining how Intelligence is enabled through

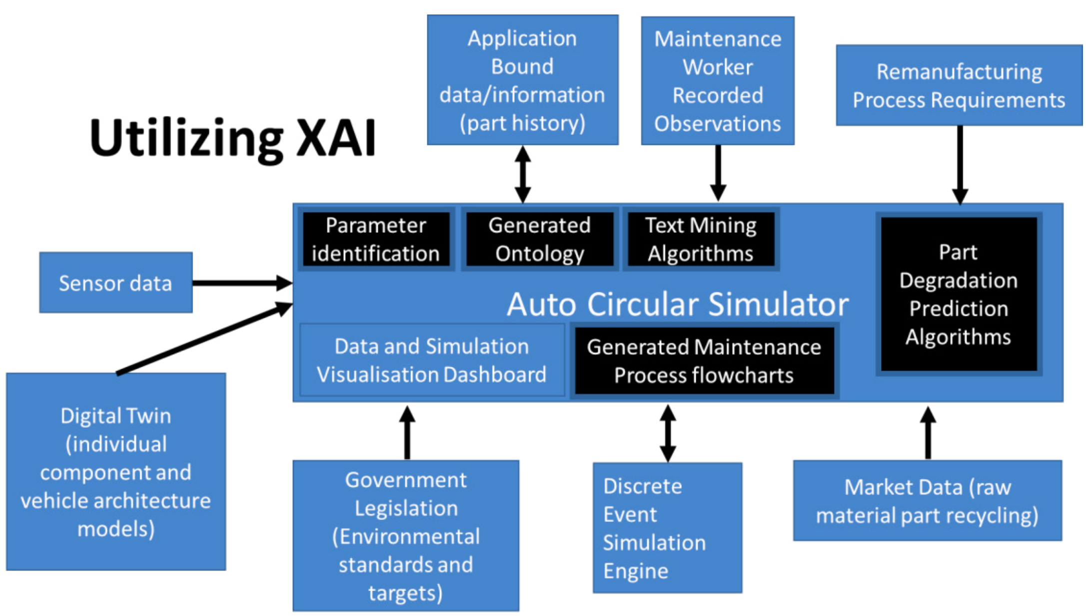

Figure 1. Auto Circular Simulator Utilization of XAI: Adapted from Turner et al. (2022).

The work of García-Magariño et al. (2019) experiments with the generation of such XAI derived explanations of knowledge learnt by a Neural Network based the input of sensed IoT derived data (within this paper XAI is also termed as Human centric AI (HAI)). The approach of García-Magariño et al., (2019) is especially instructive in the process for explaining the decision to combine different IoT sensor outputs. Hoffman et al. (2018) introduce the notion of metrics to evaluate the utility of the explanations produced by XAI systems. In concluding that the newly emerging field of metrics for XAI may differ in its implementation depending on organizational use and context, Hoffmann et al. (2019) suggest that the theory

embedded processing and utilized though the whole product lifecycle. Sallez et al. (2010) also give focus to the potential recycling stage of an Intelligent product, finding that augmenting products with information can assist is detailing their material composition (which can also be leveraged by remanufacturing and reverse logistics processes). It is the case that 'in use' data and connectivity can contribute to more efficient use of the product in terms of its environmental footprint and energy use by facilitating predictive maintenance actions. In utilizing the intelligence of assets for sustainability goals and full lifecycle considerations there still remains a challenge to facilitate the cyber physical system challenge of keeping the human in the loop of decision making. This need is perhaps paramount in decisions involving considered end of like treatments for maintained assets; one that may in part be addressed by the use of XAI narratives.

4. OPERATOR 5.0 AND XAI

In an earlier move towards human in the loop use of digital technology in industry Romero et al. (2016) proposed the Operator 4.0 vision. Seen as a move from demarcated human or automation solutions to industrial problems Operator 4.0 encourages a synergy of manual and machine skills to form human centric cyber physical systems, designed to leverage and enhance human skills while promoting social sustainability through workplace inclusion of diversity (Romero et al., 2020). Romero et al. (2016) go onto define the concept of an Intelligent Personal Assistant with the role of providing an 'interactivity hub' allowing humans to communicate with and visualize data from a diverse range of industrial information and machine systems. The operator 4.0 concept also explores the notion of voice activated control as one route of communication between humans and automation systems (Romero et al., 2016). In anticipating the use of new modes of information visualization and the increasing bandwidth of IoT connected hardware Operator 4.0 has been recently extended into the Operator 5.0 concept, centered on enhancing the resilience of manufacturing systems through the enablement of humans to work with automation solutions to provide fast resolution to disruptions in production systems (Romero and Stahre, 2021).

5. A FRAMEWORK FOR XAI USE IN HUMAN IN THE LOOP MAINTENANCE

In Turner et al. (2022) the notion of maintenance practices expressed as process flowcharts, generated from near to real time data capture of maintenance activities and part degradation prediction approaches (among other data points) was presented. In addition the semantic nature of the approach allows for validating rules to be generated and applied to maintenance predictions; such validating rules may be based on the evidence such as: past records of repairs; general statistics concerning the part type reliability; other assets the part is physically linked to when in use; recorded observations

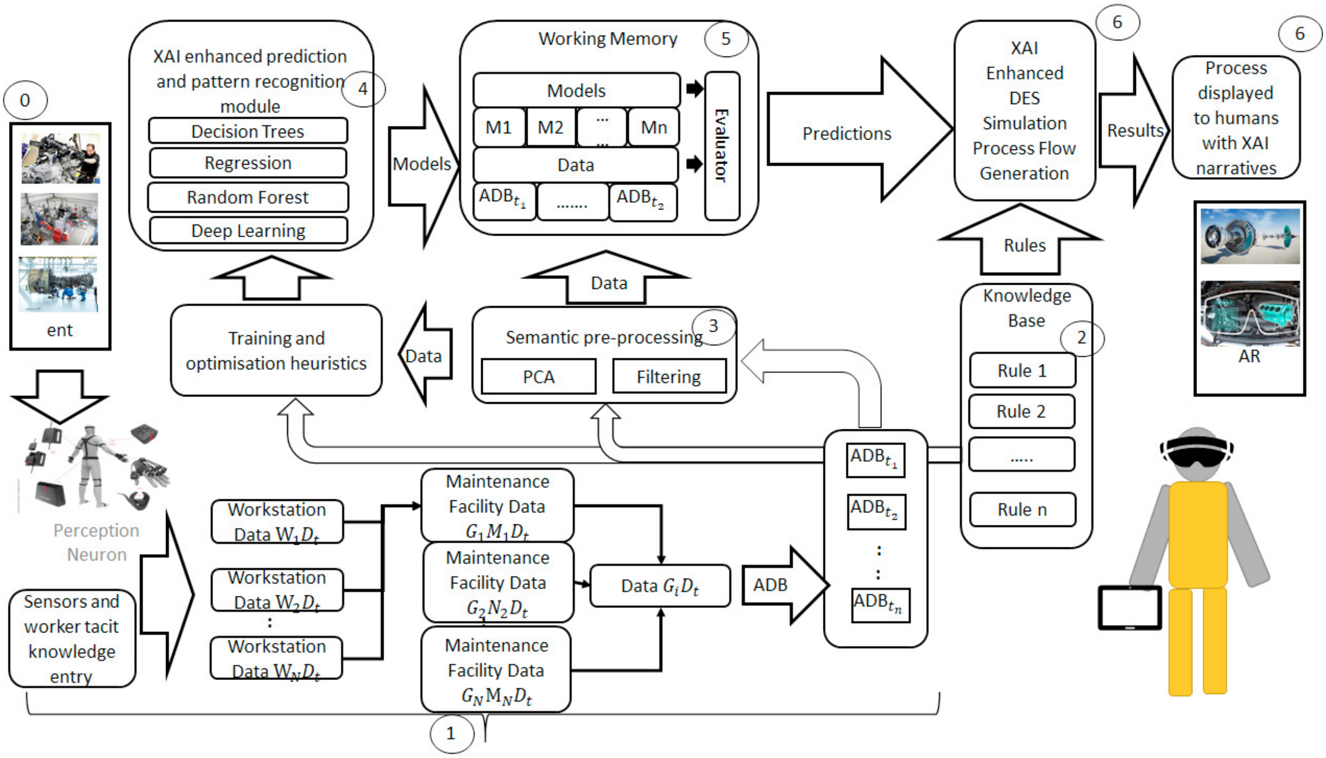

Figure 2. Intelligent and Sustainable Maintenance Framework: Incorporating a knowledge based cognitive architecture for operators (adapted from Oyekan et al. (2021b) and Turner et al. (2022)

of maintenance engineers. Data may indeed be annotated with context related information to provide linkages between potential validating evidence types when establishing the veracity of forecasted events and their suggested mitigating actions. The Auto circular simulator concept (outlined in Figure 1) allows the sustainable treatment of automotive components; where a combination of Discrete Event Simulation (DES), text mining and Artificial Intelligence is used to combine disparate IoT generated data-sources and information systems to provide an intelligent support tool for vehicle maintenance technicians.

5.1 Intelligent maintenance operative framework outline

In envisaging the next generation of this tool, integrating Industry 5.0 human centricity, the Intelligent Maintenance operative framework is put forward as shown in Figure 2 (illustrating the key data flows behind the auto circular simulator outline shown in Figure 1).

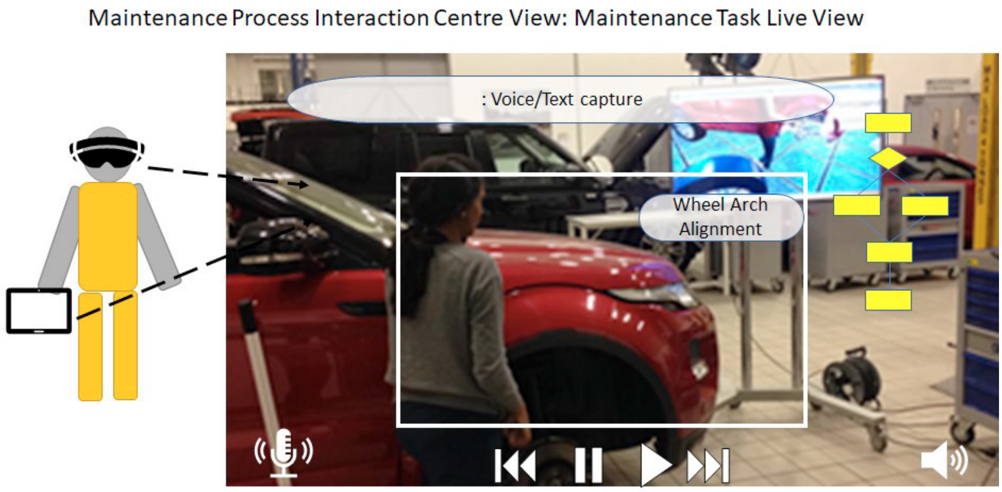

Figure 3. Maintenance Process Interaction Centre View: Maintenance Task Live View

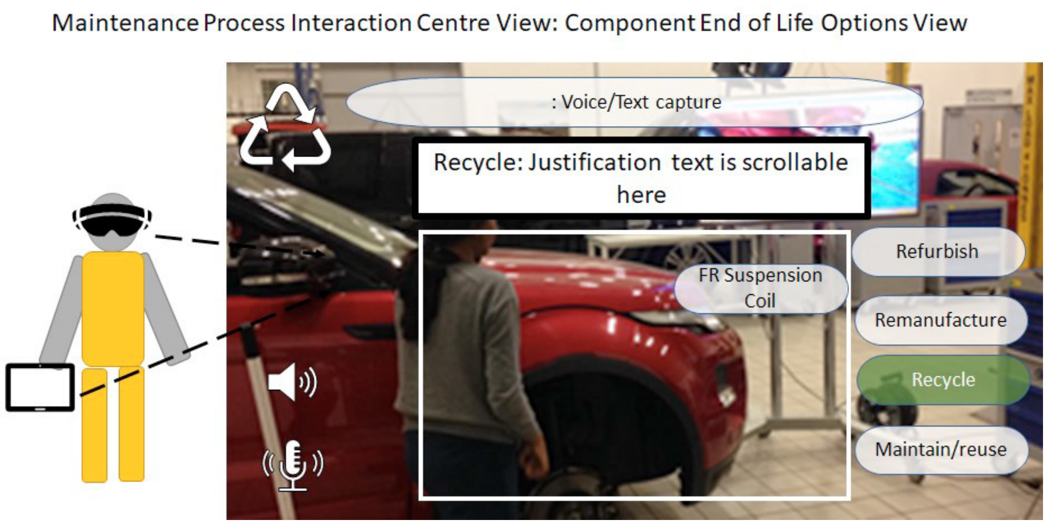

Figure 4. Maintenance Process Interaction Centre View: Component End of Life Options

Module 1 depicts the variety of data being collected from automotive maintenance facilities. The data is collected via. sensors on machines or wearables on humans. The data is tagged by machine/workstation W and time collected D. The combination of sensors in a maintenance facility, leads to facility data which is tagged according to its geographical location G, id M and time collected D. From these data collected, an aggregated data bundle (ADB) is then generated for a large manufacturer with various maintenance facilities scattered across multiple geographical locations. This data can then be stored in a database for analytics by the architecture. These data could also be augmented with a vehicle's performance data across its lifetime, so that machine learning algorithms could find correlations between maintenance process data and the impact on the vehicle's components during its lifetime

The architecture is designed in such a way that new algorithms including deep learning algorithms could be flexibly added to the architecture as they come out of the research base (module 4) while the knowledge base (module 2) provides humans the ability to introduce contextual rules to the architecture through a back loop that passes through higher management level systems (e.g. Manufacturing Execution /Enterprise Resource Planning systems) first for management approval/notification (not shown in Figure 2). These rules could be related to newly discovered sustainable practices that can be applied to vehicles. The aim of the machine learning and rules based combined approach is to achieve a synergy between machine driven data collection and processing (module 0-4) as well as human oversight (module 2). This is to ensure that humans can mitigate against the inability of machine learning algorithms to understand and make use of contextual information while at the same time making use of their strengths in processing and detecting patterns in very large data sets. Furthermore, with opaque AI algorithms such as deep learning the processes used to make decisions are not clear. Conversely, transparent algorithms such as decision trees offer the ability to be readable and understandable by a human, though lack the power of deep learning algorithms. Towards harnessing both the explainable potential and pattern detection power of AI, module 4 particularly makes use of a combination of such algorithms with the potential for a user of the architecture to apply both classes to datasets. By combining a data-driven rule extraction process (in the form of decision trees) with a human defined rule process (module 2), the foundation of XAI human centric serving capabilities is achieved in the architecture. By connecting module 2 to module 6, the rules in the knowledge base are able to be used to sanitize the predictions offered by the machine learning algorithms and the process flows generated by the Discrete Event Simulator. For example, data obtained from sensors can be used to generate decision trees that create the transparency needed to understand why and when a part fails especially in novel situations and environments in which vehicles have not been used before. This could be combined with powerful opaque AI algorithms that can extract patterns in the dataset and produce predictive maintenance regimes for automotive parts. Human knowledge can be overlaid over these results in the form of rules that define if a part should be refurbished, remanufactured, recycled, maintained or reuse based on both current safety regulations and forthcoming standards in the automotive sector. This results in contextual explainable maintenance process information with the addition of XAI derived narratives, provided to humans (module 6) through augmented reality via. goggles or tablet device. Due to the data collected and processed by the architecture, decision on whether components in a vehicle should be sustainably recycled, remanufactured or repaired would be displayed on an AR overlay for humans to make a decision. In this work a focus has been given to XAI technology and cognitive architecture of Figure 2 in realizing the Auto Circular Simulator featured in Turner et al. (2022); while the first two components were not a concept of the aforementioned research, as demonstrated in this paper, they play a central role in the realization of the auto circular simulator as a human in the loop tool for maintenance.

In Figure 3 it can be seen that the maintenance operative is able to view, via. Augmented Reality (AR) goggles or Tablet device, the maintenance activity as a process flowchart. The depicted flowchart is annotated with instructions relating to the steps in the process (which may be clicked on to reveal further narrative or provided to the worker in audio form). The entire maintenance process may be replayed to the current level of completion and steps reviewed. Interactions may also be made in the form of voice activated control and transcription. In the central square block of Figure 3 additional narrative may appear in context to the maintenance action and triggered by proximity and movements of associated parts (in the case displayed the wheel arch is being aligned). It will also be able to overlay semi opaque colors over parts as they are being aligned to dynamically indicating when correct alignment has been achieved (with a red to green transition indicating this).

As can be seen in Figure 4 the technology set put forward in Turner et al. (2020) and Turner et al. (2022) is expanded to utilize Explainable Artificial Intelligence (XAI) to provide reasoning behind changes and adaptions to generated maintenance processes, explain automated decision making as an interrogatable set of stage gate narratives, and more reliably act on and integrate the recorded tacit knowledge of maintenance workers as they complete their tasks. In Figure 4 the circularity aspects of the maintenance activity may be displayed and recommendations presented to the technician along with XAI generated narrative to provide justification for the choice. The audio transcription of human inputs can also act as a communication medium with AI technologies providing new ‘learning’ eveidence for inclusion in the base materials by the algorithms to enable the dynamic modification of maintenance process steps, maintenace scheduling and new scenario development. The ‘learning’ base materials will also act as a general knowledge capture repository (Quintana-Amate et al., 2017) allowing the context aware semantic tagging of such multimedia assets, with the possibility to also utilise montion sensors such as Microsoft Kinect (Hutabarat et al., 2016) to both capture tacit skills knowledge and provide more accurate processes for worker training.

A new generation of wearable sensors may also provide additional data points on the performance of manual tasks by capturing the physical actions of a maintenance worker. Oyekan et al. (2021a) propose the Cognitive Architecture for Wearable Sensors (CAWES) to provide a further enhanced methodology for data stream fusion of multiple wearable sensors to enable real time analysis of human ergonomics in an industrial shopfloor setting. In combining the architecture of Oyekan et al. (2021a) with that of XAI techniques it will be possible to allow machine learning techniques to annotate stages of the resolved human manual action to suggest how a complex maintenance activity may be better performed in real time. Both audio and visual prompts could be provided to the worker, in effect manifestations of the explanations given by the XAI technique, to provide ‘on the job’ guidance whilst undertaking a given task.

6. CONCLUSION

It is clear that the field of Explainable Artificial Intelligence (XAI) while a relatively new contribution in the Artificial Intelligence (AI) arena, holds much promise as a key ingredient in not just the achievement of human in the loop maintenance solutions but also in wider Operator 4/5 industrial scenarios requiring a synergy of human and machine skills. In envisioning the development of new maintenance automation systems, the empowerment of the human is a vital component; the need for understandable shared narratives in such Cyber Physical Systems necessitates a consideration of both the situation and environment of operation of the maintenance task. The ability to adapt explanations based on context awareness, such as use in teaching is different from auditing and validation activities, is an important development direction for this technology. The ability to visualize complex, often numerically based, data and translate this into appropriate context aware narrative and graphic forms is key to the next generation of human in the loop maintenance systems. While the case study in this paper focusses on the automotive industry the framework is just as adaptable to most industrial asset management uses such as those presented by production line maintenance and in the aviation sector.

This paper puts forward the Intelligent and Sustainable Maintenance Framework with knowledge based cognitive architecture for operators and illustrates it with a case study from the automotive industry. In bridging the gap between machines and humans XAI leverages the best of both worlds to provide a new level of agility to the performance of cyber assisted maintenance activities and full lifecycle consideration of assets; a notion that is necessary throughout the organization in the achievement of sustainability goals set by governments around the world in the achievement of a net zero carbon emission economy.

REFERENCES

Adadi, A. and Berrada, M. (2018). Peeking inside the black-box: a survey on explainable artificial intelligence (XAI). *IEEE Access*, 6, pp.52138-52160.

Breque, M. De Nul, L. and Petridis, A. (2021). Industry 5.0. towards a sustainable, human-centric and resilient european industry. *Publications Office of the European Union*, Luxembourg, 2021.

Garcia-Magarino, I., Muttukrishnan, R. and Lloret, J., (2019). Human-centric AI for trustworthy IoT systems with explainable multilayer perceptrons. *IEEE Access*, 7, pp.125562-125574.

Emmanouilidis, C., P. Pistofidis, L. Bertoncelj, V. Katsouros, A. Fournaris, C. Koulamas, and C. Ruiz-Carcel. (2019). Enabling the human in the loop: Linked data and knowledge in industrial cyber-physical systems. *Annual Reviews in Control*, 47, pp.249-265.

Hanif, A., Zhang, X. and Wood, S. (2021). A Survey on Explainable Artificial Intelligence Techniques and Challenges. In 2021 IEEE 25th International Enterprise Distributed Object Computing Workshop (EDOCW) IEEE. pp. 81-89.

Hoffman, R.R., Mueller, S.T., Klein, G. and Litman, J., (2018). Metrics for explainable AI: Challenges and prospects. *arXiv preprint*, arXiv:1812.04608.

Hrnjica, B. and Softic, S. (2020). Explainable AI in manufacturing: a predictive maintenance case study. In IFIP International Conference on Advances in Production Management Systems, Springer, Cham. pp. 66-73.

Hutabarat, W., Oyekan, J., Turner, C., Tiwari, A., Prajapat, N., Gan, X.P. and Waller, A., 2016, December. Combining virtual reality enabled simulation with 3D scanning technologies towards smart manufacturing. In 2016 Winter Simulation Conference (WSC) (pp. 2774-2785). IEEE.

Nahavandi, S. (2019). Industry 5.0—A human-centric solution. *Sustainability*, 11(16), pp.4371.

Nunes, D.S., Zhang, P. and Silva, J.S. (2015). A survey on human-in-the-loop applications towards an internet of all. *IEEE Communications Surveys & Tutorials*, 17(2), pp.944-965.

Li, W., Sadigh, D., Sastry, S.S. and Seshia, S.A. (2014). Synthesis for human-in-the-loop control systems. In International Conference on Tools and Algorithms for the Construction and Analysis of Systems (pp. 470-484). Springer, Berlin, Heidelberg.

Meyer, G.G., Främling, K. and Holmström, J. (2009). Intelligent products: A survey. *Computers in Industry*, 60(3), pp.137-148.

Morlet, A., Blériot, J., Opsomer, R., Linder, M., Henggeler, A., Bluhm, A. and Carrera, A. (2016). Intelligent assets: Unlocking the circular economy potential. *Ellen MacArthur Foundation*, pp.1-25.

Quintana-Amate, S., Bermell-Garcia, P., Tiwari, A. and Turner, C.J., 2017. A new knowledge sourcing framework for knowledge-based engineering: An aerospace industry case study. Computers & Industrial Engineering, 104, pp.35-50.

Oyekan, J., Chen, Y., Turner, C. and Tiwari, A. (2021a). Applying a fusion of wearable sensors and a cognitive inspired architecture to real-time ergonomics analysis of manual assembly tasks. *Journal of Manufacturing Systems*, 61, pp.391-405.

Oyekan, J., Hutabarat, W., Turner, C., Tiwari, A., He, H. and Gompelman, R. (2021b). A Knowledge-Based Cognitive Architecture Supported by Machine Learning Algorithms for Interpretable Monitoring of Large-Scale Satellite Networks. Sensors, 21(13), p.4267.

Romero, D., Stahre, J., Wuest, T., Noran, O., Bernus, P., Fast-Berglund, Å. and Gorecky, D. (2016), Towards an operator 4.0 typology: a human-centric perspective on the fourth industrial revolution technologies. In proceedings of the international conference on computers and industrial engineering CIE46 Proceedings, 29-31 October 2016, Tianjin, China, pp. 29-31.

Romero, D. and Stahre, J. (2021). Towards The Resilient Operator 5.0: The Future of Work in Smart Resilient Manufacturing Systems. *Procedia CIRP*, 104, pp.1089-1094.

Romero, D., Stahre, J. and Taisch, M. (2020). The Operator 4.0: Towards socially sustainable factories of the future. *Computers & Industrial Engineering*, 139, p.106128.

Sallez, Y., Berger, T., Deneux, D. and Trentesaux, D., (2010). The lifecycle of active and intelligent products: The augmentation concept. International Journal of *Computer Integrated Manufacturing*, 23(10), pp.905-924.

Tjoa E. and Guan, C. (2021). A Survey on Explainable Artificial Intelligence (XAI): Toward Medical XAI, *IEEE Transactions on Neural Networks and Learning Systems*, 32(11), pp. 4793-4813, doi: 10.1109/TNNLS.2020.3027314.

Turner, C. Ma, R., Chen, J., Oyekan, J., (2021). Human in the Loop: Industry 4.0 technologies and scenarios for worker mediation of automated manufacturing, *IEEE Access*, 9, pp. 103950 – 103966, DOI: 10.1109/ACCESS.2021.3099311

Turner. C. Okorie O., Emmanouilidis, C. Oyekan, J. (2020). A Digital Maintenance Practice Framework for Circular Production of Automotive Parts, Advanced Maintenance Engineering, Services and Technologies (AMEST) 2020, 10-11 September, Cambridge , UK.

Turner, C., Okorie, O., Emmanouilidis, C, Oyekan J. (2022). Circular production and maintenance of automotive parts: An Internet of Things (IoT) data framework and practice review, *Computers in Industry*, 136, DOI: 10.1016/j.compind.2021.103593.