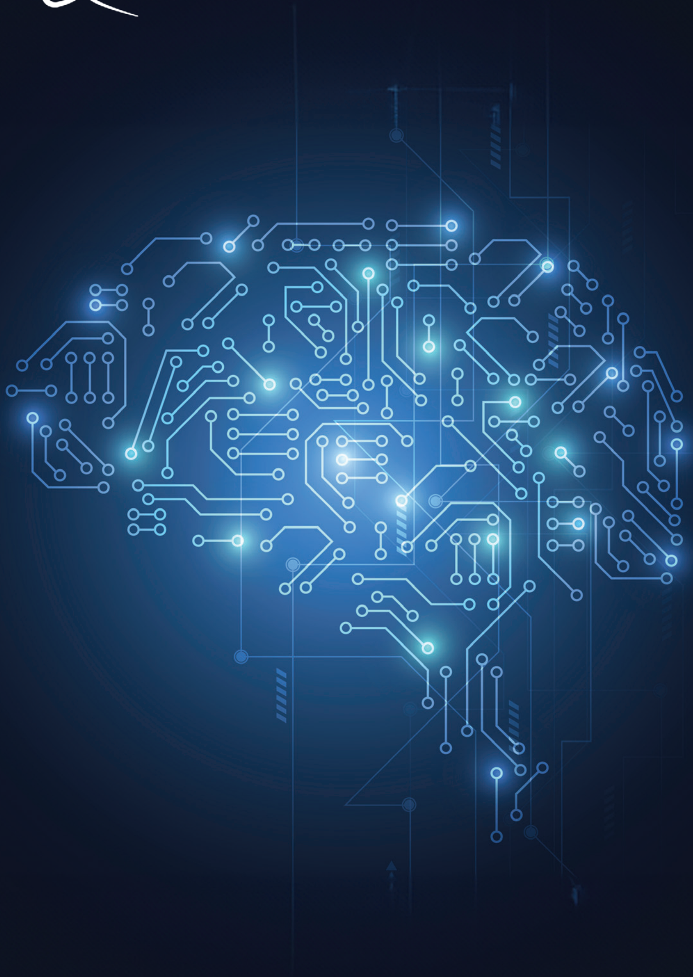
# XMANAI

MAKING AI UNDERSTANDABLE



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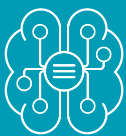
# WHAT IS XAI?

Explainable Artificial Intelligence (XAI) is a field of research that seeks to develop methods for making Artificial Intelligence (AI) more transparent and understandable to humans. XAI systems can explain their predictions and decisions in a way that is understandable to people, even if their understanding of AI is not very deep.

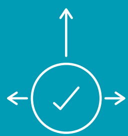
**XAI is essential for the widespread of AI systems because it can:**

Lead to improved decision-making, based on a better understanding of the system behaviour



Help to identify and mitigate biases that may be present in the data used to train the models or algorithms, hence contributing for more fair and equitable AI systems

Build trust due to enhanced transparency, accountability and understanding



## XAI and the XMANAI project

XMANAI is a European research project that is placing the indisputable power of Explainable AI at the service of manufacturing and human progress carving out a human-centric, trustful approach that is respectful of European values and principles, adopting the mentality that "our AI is only as good as we are".

Despite the many benefits that artificial intelligence brings to society and industry in general, humans typically have little insight about AI itself and even less concerning the knowledge on how AI systems make any decisions or predictions due to the so-called "black-box effect". The opaqueness of many machine learning/deep learning algorithms makes it impossible to examine them after execution to understand how and why decisions were made. The XMANAI´s objective is to make humans fully understand how decisions have been made and what has influenced them.

Based on the latest AI advancements, XMANAI focuses its research activities on making AI models, step-by-step, understandable, and actionable at multiple layers (data-model-results). The project supports the shift to a 'glass box' concept, which means that AI models can be explained to a 'human-in-the-loop' without significantly compromising AI performance.

By using appropriate methods and techniques, XMANAI can help navigate the AI's 'transparency paradox' and therefore:

a) Accelerate business adoption business adoption addressing the problematic that "if manufacturers do not understand why/how a decision/prediction is reached, they will not adopt or enforce it", and

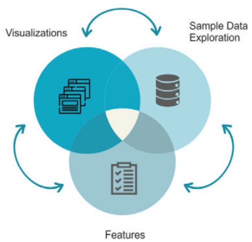
b) Foster improved human/ machine intelligence collaboration in manufacturing decision making, while ensuring regulatory compliance.

Adopting a scalable approach towards Explainable and Trustful AI as dictated and supported in XMANAI's X-by-Design approach, manufacturers will be able to develop a robust AI capability that is less artificial and more intelligent at human and corporate levels in a win-win manner.

## X-by-Design Paradigm

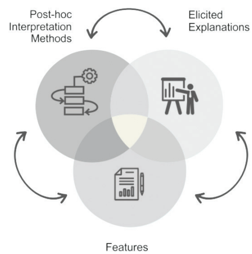
The paradigm of explainability by design (X-by-Design), a key outcome of the XMANAI project is addressing challenges associated with post hoc interpretability techniques by integrating transparency into AI models from their inception. This approach prioritizes explainability during the developmental phase, allowing AI designers, engineers, and data scientists to construct models that inherently offer transparent insights into decision-making processes.
X-by-Design advocates for embedding explainability into the design process of AI systems, aligning with established concepts like privacy-by-design and security-by-design. It emphasizes the responsibility of companies to assess the potential impacts of AI systems from the outset, defining rules these systems must adhere to, and mitigating the need for complex and often unreliable post hoc explanations. This paradigm shift represents a crucial advancement in AI development, ensuring the responsible implementation of technology and safeguarding against unintended negative consequences.

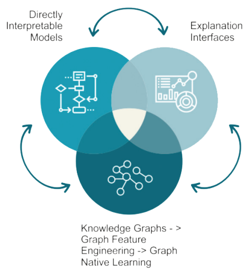
To transition towards an X-by-Design paradigm, XMANAI views and supports explainability under three (3) interlinked and collaborative perspectives:




**1)** Data Explainability, which focuses on understanding data semantics and structure to gain insights, utilizing interactive exploration and visualization to monitor potential biases or drifting issues.

**2)** Model Explainability that concerns understanding how different AI models work. This involves two main parts: understanding how a model works in general for all predictions (global interpretability), and understanding how it makes a specific prediction based on certain data points (local interpretability). Various techniques can be used to achieve this, such as explanations by simplification, feature relevance, or using models that are natively easier to understand. Some common techniques include LIME, SHAP, Anchors, Partial Dependence Plot,Counterfactual Explanations, and CAMEL.




**3)** Results Explainability, which facilitates a shared understanding of results, utilizing post-hoc explanations including visualizations, text explanations, example-based explanations, and counterfactual explanations to translate results into actionable insights.

The X-by-Design process starts with a data gathering step to collect information about the explainability needs from the industrial user. Specific workshops or questionnaires can be used to explore the problem considered and the use case to be addressed. In a second step, X-by-Design requires a formalization of explainability user stories in the form of “As a [user], I want to [goal], so that [benefit]”, specifying the associated acceptance criteria that would satisfy the implementation. This approach to provides a great deal of context to developers and consultants working on the system specification. With the explainability requirements it is then possible to design the explainability solutions in terms of data, model, and results explainability as previously described, and ending with a proposal of explainability interfaces for demonstration. The approach is concluded with the actual development of the designed AI solutions using the XMANAI platform components and the specific explainable interfaces designed.

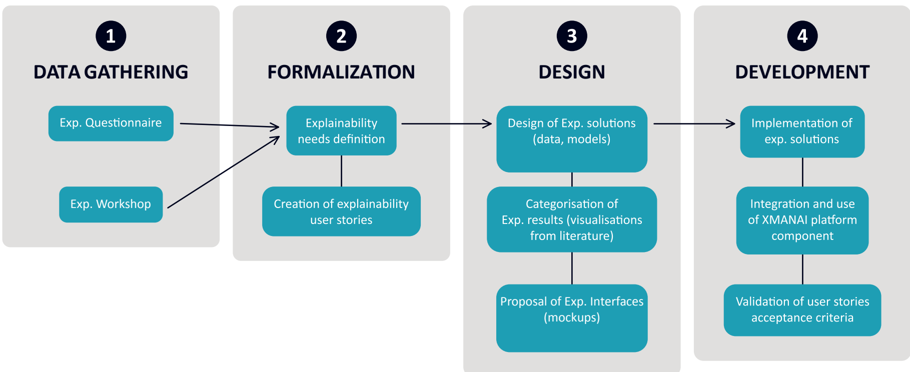



*Figure 1: X-by-Design Process*

# PLATFORM OVERVIEW

XMANAI aims at becoming a reference in manufacturing, with an user- driven, industry-led mentality and a market-oriented approach, enabling different actors to address the inherent AI-related hurdles in a realistic and tangible manner:

- Data scientists – to understand the problem at hand, create AI models and derive actionable insights frm data in different application domains.
- Data engineers – to build the necessary underlying infrastructure to collect and prepare data, and to deploy AI models in a scalable manner.
- Business experts – to understand the results of an analysis in a tangible manner and take more informed decisions depending on the pilot case.

## Main Results

One of the main results is the XMANAI Core Platform, which is fully aligned with the manufacturing needs and idiosyncrasy, acting as a single reference point of access both for AI and for manufacturing value chain stakeholders, and allowing a seamless interoperation with on-premise environments through open standard- based APIs.

The platform is a comprehensive suite of tools and services for developing and deploying XAI solutions in manufacturing, including:

- A library of baseline and pre-trained XAI models;
- A toolkit for developing custom XAI models;
- On-premise environments for execution in stakeholder's private clouds;
- Manufacturing apps portfolio which is composed of AI manufacturing intelligence solutions that are effectively solving specific manufacturing problems;
- A manufacturing data model and knowledge graph for enhanced data interoperability;
- Data assets available through the XMANAI marketplace.

## Technical Architecture and Components

The XMANAI platform's services are developed and integrated into eight distinct bundles, ensuring seamless integration through well-defined interfaces. These bundles facilitate intercommunication among the services and contribute to the overall functionality of the XMANAI platform, and include the:

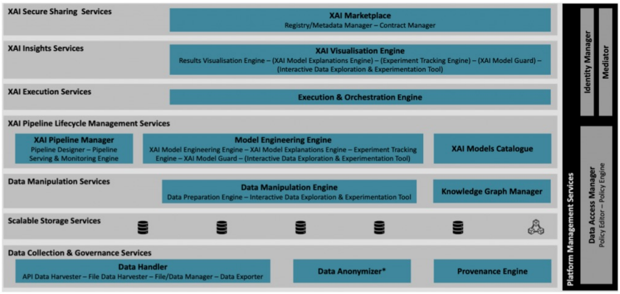



*Figure 2: Overall XMANAI´s Platform architecture*

• **Data Collection & Governance Services bundle -** It ensures consistent and well-managed data collection by configuring and executing appropriate data handling processes. It securely and reliably collects data assets and incorporates a provenance mechanism to track their lifecycle.

• **Scalable Storage Services bundle -** It facilitates the persistence of platform assets based on their types and storage locations, and provides metadata indexing to optimize query performance and enhance data discoverability.

• **Data Manipulation Services bundle -** Its core functionalities include data explainability and feature engineering. It enables the derivation and harmonization of knowledge from available data based on the XMANAI data model, and prepares the data for ML/DL applications, allowing its usage in training XAI models and executing XAI pipelines.

• **XAI Execution Services bundle -** It is responsible for executing XAI model/pipeline experiments during the experimentation phase and deploying XAI pipelines in the production phase based on user-defined schedules. It monitors and tracks the execution status in the Secure Execution Clusters and/or the On-Premise Environments, ensuring the storage of model/pipeline results and associated metrics.

• **XAI Insight Services bundle -** It facilitates collaboration between business experts and data scientists and supports gaining insights throughout different phases of extracting manufacturing intelligence. It incorporates the XAI Visualization Engine, which offers novel dashboards and diagrams to visually represent data, XAI model results, explanations, and insights, thereby supporting the entire experimentation process.

• **XAI Lifecycle Management Services bundle -** It manages XAI pipelines, encompassing collaborative design, validation, and handling of the pipelines. It integrates various functionalities such as data preparation, model engineering, and explainability, as well as training, explanation generation, management, tracking, and evaluation of XAI models, considering performance and security aspects.

• **Secure Asset Sharing Services bundle -** It enables cataloging and trusted sharing of data and AI models across various manufacturing organizations and/or users. These functionalities are provided through the XAI Marketplace.

• **Platform Management Services bundle -** Its responsibilities include access control functionalities for data assets based on providers' preferences, centralized user management, and authentication mechanisms for the platform.

## How to use the XMANAI platform

To use the XMANAI platform, you must create an account, and after that, you can access the platform's features and services.

The **Data Import** menu item currently offers data harvesting operations that enable the creation of new datasets from existing files.


The **Experimentation** menu item provides access to XAI exploration and experimentation operations, using the data available and the notebook environments provided by the XAI platform.

By using the **Pipelines** menu item, the XAI application operations can be accessed and the design can be enabled, so the execution of advanced AI pipelines tailored to the needs of each stakeholder.

The **Asset Management** menu item provides access to datasets, models, and results management operations that enable the complete lifecycle management of assets with multiple options available to each asset owner.

The **Catalogue** menu item allows access to the assets catalogue operations, which enable the search and acquisition of assets through the platform's marketplace.

Through the **Admin** menu item, platform administration operations can be accessed and facilitate the organization and user management activities performed by either the organization's administrator or the platform administrator.

## Benefits of using the XMANAI platform

The XMANAI platform offers several benefits to manufacturing businesses, including:

**Improved transparency**
It helps manufacturing businesses increase the transparency of their AI systems by explaining how their AI systems are making decisions.

**Increased reliability**
By identifying and fixing biases in AI systems, the XMANAI platform can aid manufacturing companies in enhancing the reliability of their AI systems.

**Enhanced trustworthiness**
The XMANAI platform can help manufacturing businesses expand the credibility of their AI systems by building trust with their customers and stakeholders.

**Reduced risk**
The XMANAI platform can help manufacturing businesses reduce the risk of using AI systems by explaining how their AI systems are making decisions and identifying and fixing biases in their AI systems.

# PILOT USE CASES

XMANAI conducted four industrial pilot demonstrators to showcase the effectiveness of its X-by-Design approach and XAI solutions in real-world manufacturing settings.

These pilot cases address different manufacturing challenges, posed by the following companies: CHN Industrial, Ford Motor, UNIMETRIK, and Whrilpool.

CNH Industrial is a world-class equipment and services company, a global leader in the design and manufacturing of agricultural and construction machines, that employs more than 64.000 people in 66 manufacturing plants and 54 R&D centers in 180 countries. The collaboration with European partners of the XMANAI project was developed within the San Matteo plant, located in Modena, Italy. It is the most relevant R&D unit in the field of tractors in Europe, using the most advanced technologies for design and engineering purposes.

## PROBLEM ADDRESSED AND PILOT OBJECTIVES

The pilot focuses on Modena Plant which is currently manufacturing 60K APL and APH (All Purpose Low – High Tractors) drivelines used to equip all tractors assembled in CNHi plants worldwide. Today, production lines are affected by unplanned and planned stoppages that reduce their availability. Such stoppages are typically required to replace worn or faulted components (i.e., tooling), and when a machine stops, maintenance operators must exclude different parts of the machine step-by-step to get to the faulty component and understand where the fault occurred, and which anomaly caused the stoppages. As a result, operators waste significant amounts of time troubleshooting the faulty component and delay the order for replacing the component. Moreover, if the operator is not able to restore the machine, it is necessary to call for external maintenance operators, slowing down the process even more.


*Figure 3: CNH plant: New Holland operators in production line*

The main CNH's objective is the optimization of the production plant operations using XMANAI, using XAI to quickly identify the problem, addressing downtime issues and quickly restoring machinery and minimizing production losses. XMANAI ingests and analyses real-time and historical data to provide recommendations to operators, optimizing production lines and reducing costs. The platform creates a data pipeline, trains XAI models, and generates knowledge graphs to improve data management and decision-making. The XAI algorithms suggest maintenance actions based on sensor data, emphasizing the importance of explainability to ensure operators understand and trust the suggestions. The goal is to enhance machine performance by automatically collecting quality data and providing actionable insights to identify and address potential issues.

## ANOMALY DETECTION WITH AR SUPPORT USE CASE

The project is performing anomaly detection analysing real-time and historical data about the status of the CNC machine center to provide simplified suggestions to operators, optimizing production lines, and reducing costs.

A twofold benefit is verified:

**1.** Detect where the fault occurs, so that maintenance operators know which component is responsible and why, and can replace immediately the faulty part (for faster recovery);

**2.** Determine which anomaly caused the failure, so that the operators can track the occurred anomaly, reducing troubleshooting time and allowing them to focus on the actual cause, hence reducing recovery time.


*Figure 4: Production timeline Anomaly Detection*

The overall explainability design process resulted in the development of an interface for the manufacturing Web Application (App), shown in Figure 5. This App is specifically designed to provide transparent and interpretable explanations for the outputs and decision-making processes of AI systems. It includes features such as displaying active sensors, alarms, and trends of sensor data, and enables users to gain insights into the reasoning behind AI-generated outcomes. The App bridges the gap between the complexity of AI algorithms and the need for human understanding and trust. In detail, the 'Sensor Values' tab ranks sensors by criticality and allows to view trends over time, as well as provide feedback on the platform's AI-generated suggestions. Additionally, an augmented reality application assists workers in maintenance procedures, with a focus on intuitiveness and explainability.

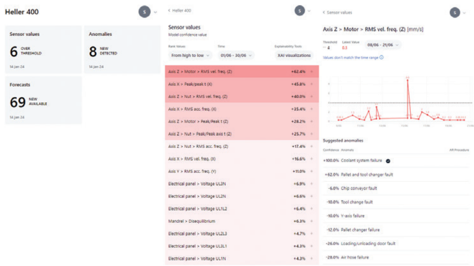



*Figure 5: Home screen; Sensor values screen; Sensor details*

## FORECASTING USE CASE

Forecasting with AI involves utilizing advanced algorithms and machine learning techniques to predict future trends, behaviours, or events based on historical data patterns. By analysing vast amounts of data, AI-powered forecasting models can adapt and learn from new data inputs, continuously improving their accuracy over time. Considering the end user would not blindly trust the results, all the potential of AI-based forecasting would be wasted without XAI.

With the introduction of forecasting in the XAI platform to optimize the production process, the maintenance operators will be helped to anticipate the downtime of the machine through the support of **XAI suggestions** that will be based on the values of the sensors installed and the historical downtime data. Maintenance operators will be ready in advance to tackle the anomaly and understand when, where, and why future faults may occur, to avoid micro-stops and prevent them.

A double benefit is achieved:

- **Detecting when and where to order the piece in advance and replace the worn component before the faults occur**
- **Knowing why to allow production managers to take concrete actions to reduce the likelihood of errors occurring again.**

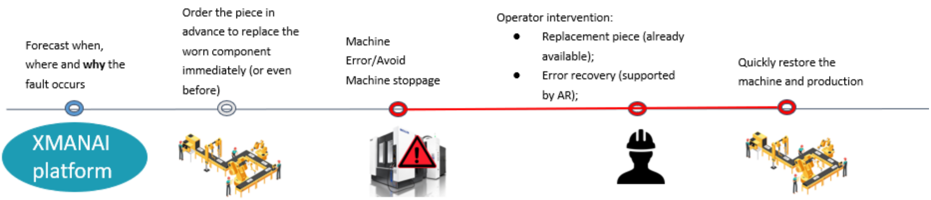



*Figure 6: Production timeline Forecasting*

Prediction of possible issues are integrated into the XAI Web Application, as shown in Figure 7. By adding the forecasting section in the App maintenance engineers have a clear view of the actual status of the machine and the potential failures. The history section of the App allows the operator to analyse the history of the most critical values for the machine failure and have insight on projection of critical values based on the historical trend. Displaying sensor values close to a dynamic threshold through a given time enables the user to order components or plan maintenance ahead of time, all using XAI.

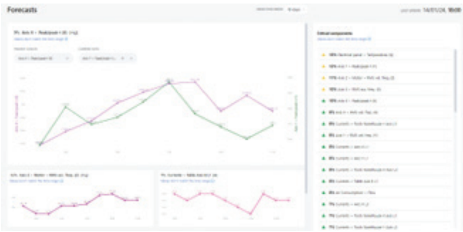



*Figure 7: Forecast with suggestions*

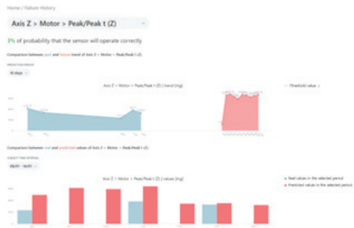



*Figure 8: XAI web-app history page*

The user is helped in understanding the relationship between sensor data and machine downtime. The trained algorithm provides scheduling suggestions to the production manager to improve the scheduling in the Plant Management System (PMS), and visualization tools are used to help operators understand the AI outcomes, promoting inspection and traceability of actions undertaken by the AI systems.

## RESULTS

The benefit that XMANAI brings to CNH is, in short, time-saving during the troubleshooting procedures. Approximately a time saving of 30 percent or more passing through the actual status to the first use case and another 10% passing through the first to the second. So XMANAI for CNH means a visible reduction of the time to reach the faulty part saving costs for the company.

Other benefits the company expects to gain from using XMANAI are as follows:

- Reduce emergency maintenance
- Reduce time/errors in machinery operations (maintenance/set-up/troubleshooting)
- Trust in XAI providing reduction of workload/stress of operators

The added value of XAI platform is the explainability associated with artificial intelligence. The evaluation of the platform through the questionnaire shows a positive impact of the XAI implemented in industrial environment. In fact, looking at the ratings recorded during the questionnaire, Figure 9, for the validation of the XAI Web-app, the explainability plays a key role.

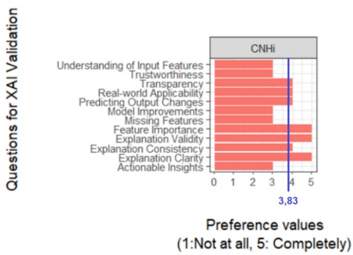



*Figure 9: Evaluation XAI platform*

Ford Motor Company is a global automotive and mobility company. The Company's business includes designing, manufacturing, marketing, and servicing a full line of Ford cars, trucks, and sport utility vehicles. Ford plants and offices are located in every region of the world, employing in 2020, around 186,000 people. In total, there are 6.883 employees and we produce 267k vehicles per year. The pilot of the project focuses on the engine plant located in Valencia, Spain.

The engine plant is currently the only Ford plant in Europe responsible for manufacturing the Duratec Ecoboost 2.0 and 2.3L engines, which are used to equip the vehicles that Ford will assemble in its assembly plants worldwide. The average annual production of the plant is 324K Engines, that in addition to shipping engines, also ships mechanized engine components like a Cylinder Block, Cylinder Head, Crankshaft and Camshaft (600K sets/year) to the Cleveland.

## PROBLEM ADDRESSED AND PILOT OBJECTIVES

The XMANAI Ford trial takes place at the Valencia engine plant (Spain-Valencia) and focuses on managing the complexity of manufacturing in terms of variability. The plant is working with weekly batches, managed manually using the expertise of MP&L (Material Planning & Logistics) and production staff. Currently, the assembly line is manufacturing 25 different derivatives (i.e., engine types) depending on the vehicle in which they will be installed. Apart from the 4 engine components that are manufactured in Valencia, each of these derivatives needs different components such as the engine crankcase, fuel pump, oil pump, clutch, and so on.

*Figure 10: Ford, Valencia Engine Plant*

Currently, the performance of the entire plant depends on the correct planning of the batches and the “MIX” that the planning engineer has scheduled based on customer demand and his experience. Furthermore, line production depends on the shift foreman’s decision to minimize planned stoppages and failures during the shift.

To improve this scenario and achieve better plant performance, Ford is considering the inclusion of an XAI system with capabilities to help operators and engineers choose the best decision at any given moment, improving line availability and efficiency.

## HOLISTIC OVERVIEW OF THE PRODUCTION USE CASE

**Holistic overview of the production with real-time representation of the production line, unwanted scenarios alert system and workload simulations.** This use case is divided in three different tasks:

• **Real-time representation** of the production lines, visualizing the status of each of the operations, whether they are automatic operations, manual stations, warehouses and so on. From this representation, a **prediction of the number of the total engines** will be produced within a production shift. If there are **deviations from the expected number** of engines and the predicted number, it will be important to identify which elements of the line are contributing to this deviation. This information will be useful for the users to infer the root causes of the deviation and to provide a quick response.

• **A system for alerting of unwanted situations** that may lead to loss of line efficiency, based on real-time information provided by different data sources. Similarly, to the first point, the explainability needs here are the same.

• **Simulation of process changes.** This task focuses on determining what would happen if some of the parameters of the production process were changed, using the data learned from the operation of the production line, machine states, efficiencies, cycle times per model, etc. For example, if the cycle time of a station for a particular model is increased, how this would affect the overall view of the line.

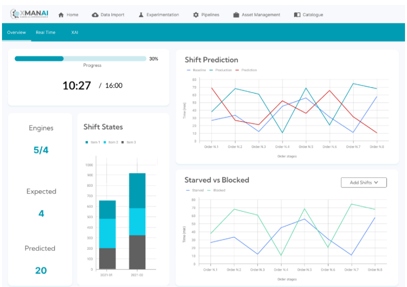



*Figure 11: Real time representation of production and its prediction*

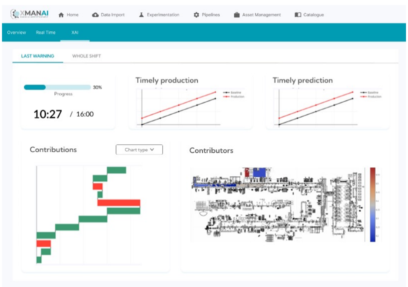



*Figure 12: XAI diagram of the latest prediction*

## AUTOMATED PRODUCTION PLANNING USE CASE

This use case consists of developing an intelligent planner that considers the production plan, customer plant demand, available components, current production on the different lines, and so on. With all this information, the planner will recommend which batches should be made on which lines. The explainability comes here through the comparison of different plans and understanding why one is better than the others considering a set of reference metrics.

The Material Planning & Logistic Engineer needs to know "why" it is the best plan of production as this is very important for the plant. This is the key, so we need explainability; conventional artificial intelligence is of no use to us.

We need to update the constraints on production data of the last shifts as the line is constantly changing and fixed constraints do not reflect the current situation. Moreover, we need to check the availability of parts and the plan of production to create the best mix of production based on the current constraints.

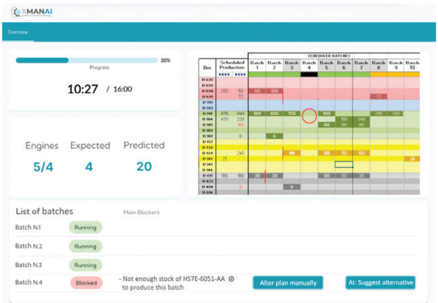



*Figure 13: Intelligent explainable planner web app*

## RESULTS

The utilization of XMANAI at Ford not only allows for the integration of cutting-edge algorithms in data analysis through XAI but also brings about tangible benefits for the plant in terms of two key performance indicators:

Firstly, it enhances **Availability** by significantly reducing downtimes for the manufacturing machines in the implementation of the first use case. This improvement directly contributes to maximizing operational efficiency and ensuring a smoother workflow.

Secondly, it elevates Line **Efficiency** by optimizing scheduling to achieve the best mix and increase overall production output. By reducing over cycles during the second use case implementation, the plant can operate at peak performance levels, thereby enhancing productivity and minimizing resource wastage.

# UNIMETRIK
METROLOGY AND CALIBRATION

Unimetrik is a Spanish Metrological Service company, oriented to offering solutions for the industry related to Calibration, Measurement, and Metrological engineering, and is currently exporting its technology in Europe and other relevant industrial countries all around the world. Among the metrological solutions currently offered by UNIMETRIK, the most relevant are the Metrological Studies utilizing the M3 software (the optical measurement system used to capture and analyse point-clouds) that are provided for testing the tolerances of industrial parts and components by working with different instruments and methods taking into account the accuracy required in each case.

## PROBLEM ADDRESSED AND PILOT OBJECTIVES

Companies dedicated to manufacturing parts and components for the automotive, aeronautical, energy, etc. sectors are receiving dimensional quality requirements and tolerances from large companies that cannot be achieved with traditional methods. Optical technology is currently being imposed for the realization of dimensional quality controls since it allows the acquisition of a large amount of information in a much shorter time than probing technology. With this optical technology, the number of pieces controlled is much higher. On the other hand, the amount of information that is handled is larger, a point cloud of a car door can have 15 million points; therefore, the management and calculation algorithms have to be optimized to the maximum.

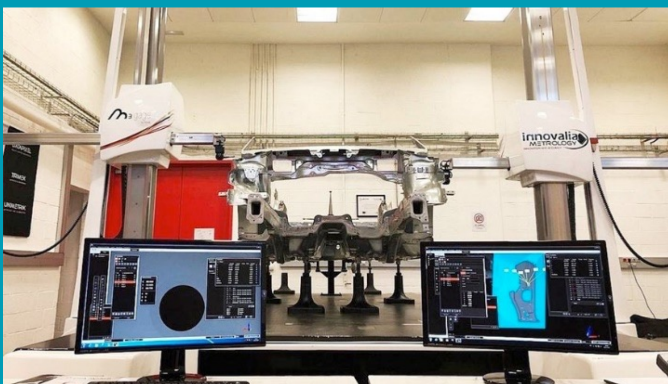



*Figure 14: Manufactured part under metrological analysis*

The UNIMETRIK pilot focuses on optical measurements for machinery components using M3, high-performance software for capturing and analising point clouds. However, this parameterizable software provides different results depending on the expertise of the operator, and as it is designed as a “black box”, it makes it difficult to verify those results and the process behind them. Before starting programming the M3 software, it is necessary to design a strategy that depends on numerous characteristics of the physical part and parameters that the manufacturer requires.

Usually, it is necessary to prepare a so-called measurement plan for each part by observing its characteristics and establishing the key scanning parameters to capture the Point Cloud. On top of that, this measurement plan is designed only tacitly profiting from the information that previous similar projects have with the object of study. Not only it is a waste of information, due to the “know-how” from previous projects being difficult to preserve, but also a waste of time, since it requires metrologists with relatively high experience, and this can be traduced as a gap in the process improvement and a suboptimal process yield.

The main goal of UNIMETRIK applying XAI for smart semi-autonomous hybrid measurement planning is to increase the efficiency in the measurement plan definition by reducing errors and speeding up the execution of the measurement, as well as predict, based on certain key parameters, the level of reliability of the result.

## OPTIMAL PARAMETERS USE CASE

The UNIMETRIK demonstrator use Explainable AI to reduce the time invested in the measuring process and to increase the accuracy of the measurements performed with M3.

A double benefit is achieved:

- The XMANAI platform contribute to “reuse” relevant information such as key parameters value configuration from previously performed jobs.
- XMANAI help metrologists in the identification of the correct values for the scanning parameters and understand why and how they impact the quality and accuracy of the measurement.

Both the design of the measurement plan definition and the identification of the key parameters involved in the configuration of the scanning device are iterative processes, where after a preliminary scan and the subsequent point cloud, the metrologist based on his/her experience needs to redefine the plan and the key parameters to reduce the deviation from the measurement and the real part.

Experienced metrologists with extensive experience can identify which regions of the part/component are the most relevant to be measured, and so, they are the ones that can adequately define the measurement strategy in the M3 software. This generates different results (accuracy level) and different time investments on the same measurement while performed by a senior metrologist and a junior metrologist.

Additionally, different values for scanning main parameters (such as Point Cloud lateral density, scanning direction, and exposure time) result in measurements with different quality and accuracy.

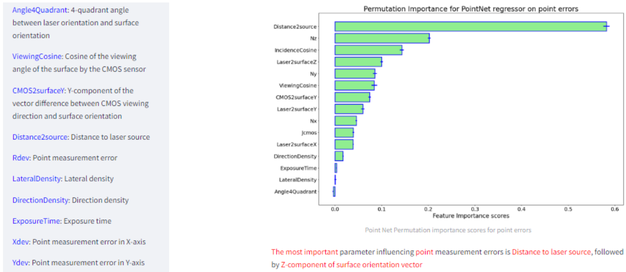



*Figure 15: Explanations of the impact of each parameter on the accuracy of the measurement*

## POINT CLOUD OPTIMISATION USE CASE

UNIMETRIK is looking for an "Explainable Optimal Cloud" in this use case for the XMANAI platform. It is aimed at generating a reduced optimal point cloud that provides the best accuracy in the following analysis and processing of that point cloud. The manufacturing application that is being developed, recommends the best cloud to perform a specific geometry measurement. For instance, the measurement of a diameter in a sphere or a cylinder. The explanations in this use case should offer information on how the optimization over the point set impacts the accuracy of the final measurement.

The XMANAI manufacturing application provides a key benefit to UNIMETRIK based on the point cloud optimization.

Nowadays only experienced metrologists can identify which regions of the piece to be measured are the most relevant and so, they can define accurate point sets. The XMANAI platform helps in the knowledge transfer process to junior metrologists by not only optimizing the point cloud but also explaining the impact of those specific point sets on the final accuracy of the measurements.

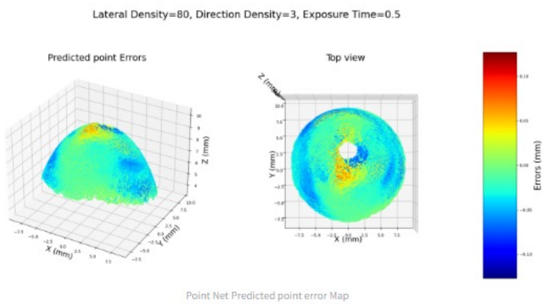



*Figure 16: Global Deviation map or deviation from the surface*

## RESULTS

The benefits that the XMANAI platform and the manufacturing application that is being developed for UNIMETRIK are based on efficiency and accuracy, which are the main characteristics of the metrology as a quality control process for manufacturing. By applying both key parameters and point cloud optimization provided by XMANAI, UNIMETRIK has been able to reduce the time invested in defining measurement plans by 12 % and to reduce the errors of the measurements by another 8 %, which has a relevant impact in the efficiency of the new explainable process.

It is highly remarkable the added value that the XMANAI platform is offering to the organization. Using explainable artificial intelligence, and the XMANAI platform, junior metrologists in UNIMETRIK effectively define a measurement strategy based on the understanding of the impact that their decisions have on the accuracy of the measurement. This is the actual knowledge transfer process that the organization needs.

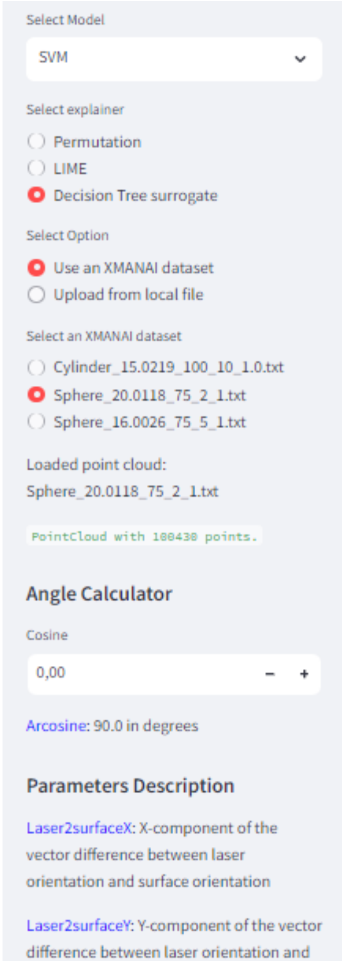



*Figure 17: UNIMETRIK manufacturing app main interface*

Whirlpool Corporation is the world’s leading kitchen and laundry appliance company, with approximately $19 billion in annual sales, 78,000 employees, and 57 manufacturing and technology research centers in 2020. With a sales presence in more than 35 countries and manufacturing sites in 5 countries, Whirlpool owns its Centre of Excellence for Research in Italy, in Cassinetta, (Varese district), and in Fabriano (Ancona district), employing researchers and technicians working on the development of innovations which are transferred to all Europe, Middle East and Africa businesses of the group.

## PROBLEM ADDRESSED AND PILOT OBJECTIVES

In the XMANAI project, the pilot’s scope has been extended beyond pure manufacturing to cover an important business challenge like sales demand forecasting: the purpose of XAI is to provide a clear explanation of the business dynamic of a D2C (Direct To Consumer) market to achieve a better control on production planning and better results in terms of sales, margins and customer satisfaction.

D2C is a business channel only recently activated by Whirlpool in European markets. It consists in the direct sale of Whirlpool products, within a defined range and brand portfolio active for that specific country, to a final consumer through a web portal. Due to the novelty of this business channel and due to the complexity induced by Whirlpool demand-driven production planning process, the capability to effectively forecast the D2C demand and to acquire a deep knowledge of the business dynamics are crucial for the success in this innovative and challenging market sector. Any misalignment in quantities, type of product or requested availability date will impact on the capability of the whole integrated supply chain to achieve its mission: “the right product in the right quantity in the right time” to customers.

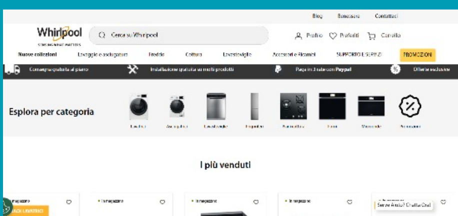



*Figure 18: Whirlpool’s D2C portal*

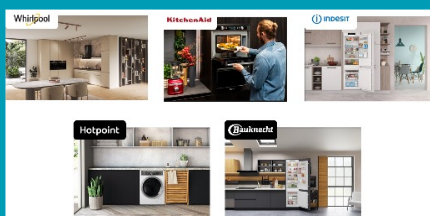



*Figure 19: Whirlpool’s brands*

The reliable demand predictability is not the only result expected from the demonstrator: the knowledge of demand dynamics and of the explanation of some forecasting effects, is very important in order to empower business stakeholders in driving and developing the business itself.

## DEMAND FORECASTING USE CASE

The primary use case is about the generation of demand forecasts in the D2C market, generating clear evidence of expected sales by product and date, to properly configure the supply chain process ensuring the necessary product availability.

The following benefits are in hand:

- The central demand planning team benefits from AI's support in making the best decisions to supply the right product, in the right quantity, at the right time, maximizing customer satisfaction, and minimizing the value of product inventory.
- The D2C marketing and sales team benefits from this information in properly executing market actions (prices, promotions, range of products offered, etc.) to maximize margins and increase profit.

Definitively, this objective is not the most important as the XMANAI platform is expected to offer the users the possibility to get explanations about the generated forecast, further supporting the decision-making process and deeply understanding the dynamics of the business behavior. The key enabler of AI adoption in the mid-long term is, without any doubt, the "trust" that users must achieve to proficiently interact with the system, and this is mandatory to pass through the XAI as the capability of the AI system to explain the reasons of a specific result. The XAI functionality allows the users to understand the correlation among the different features, generating the forecast result and directly experimenting with the effect of each of them on the outcome. This enables a deep understanding of the features that may be driven to achieve the expected sales results, leading to higher business performance and customer satisfaction.

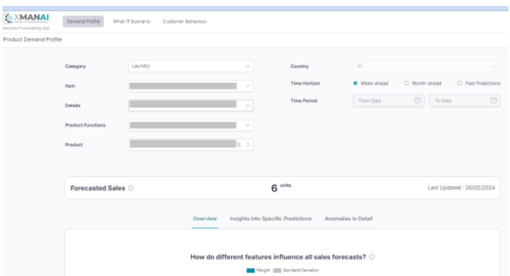



*Figure 20: Main functionalities in XMANAI Manufacturing App*

XMANAI platform offers the users not only the possibility to get access to a reliable forecast of sales per each product in a specific time horizon (next week or next 4 weeks), but it also discloses the possibility to see which the main features are impacting forecasted value, as shown in figure 21.

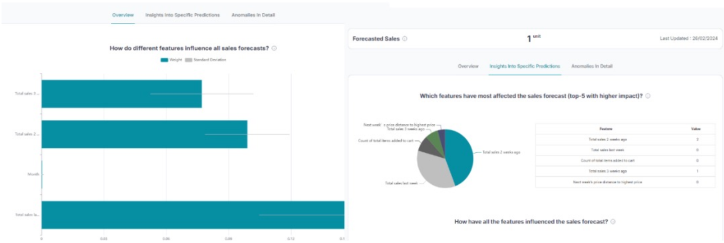



*Figure 21: Demand profile functionalities: the impact of the features on the forecast*

This information is important as some of these features may be controlled by users applying specific actions like changing selling prices, launching promotions, modifying the website to retain potential customers longer on a specific page, and so on. The visibility of the type of impact for each feature, and not only the entity, is important as well to ensure that the actions that users may adopt drive in the desired direction. Knowing if a feature may push up or down the forecast provides actionable information for users, as shown in figure 22.

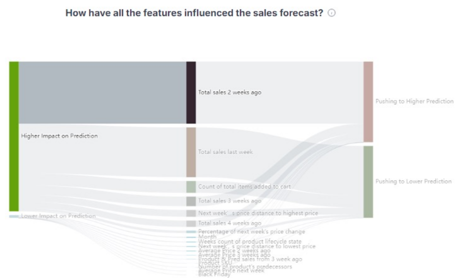



*Figure 22: Demand profile functionalities: which features may push forecast up*

The system may also provide an alert in case of "anomalies" identified in the forecast profile, as shown in Figure 23, which may be used to further investigate in advance hidden phenomena that may create potential issues in products offered to customers. Users to better understand the root causes and take mitigation or sustain actions, if needed can further investigate these anomalies.


*Figure 23: Demand profile functionalities: evidence on anomalies*

The platform also offers the possibility to simulate these actions and to see the effect of these changes on forecasted value with “What if” functionality, which may be used to envision what happens to forecast in case of changes applied to one or more features or to show which is the expected values of some feature to ensure a desired forecast. The generated scenarios may be also saved and analyzed to better decide action plans, as shown in Figure 25.

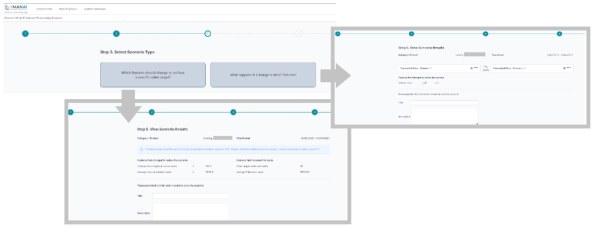


*Figure 24: What if functionalities: simulation on actionable features effect*

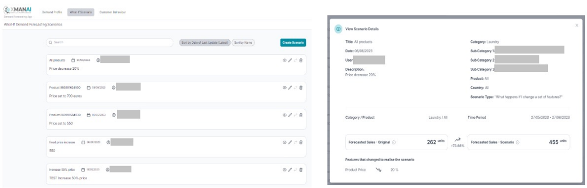


*Figure 25: What if functionalities: scenarios saving and comparison*

Finally, the platforms may offer users visibility on patterns in sales or on correlations among different features, which increases their knowledge of business dynamics. The XMANAI functionality offers the possibility to deep dive into the forecast and historical data to have full visibility of the behavior of the products in the offered range, as shown in Figure 26. The functionality also offers the possibility to visualize the correlation between some key features and the sales result in the past, as shown in Figure 27, to provide interesting tips on actions that may be executed on the sales website.


*Figure 26: Customer Behavior functionalities: Deep dive into forecast and history details*


*Figure 27: Customer Behavior functionalities: sales patterns details*

## RESULTS

The preliminary results of the first demo session held with users confirmed the validity of the visualization dashboard developed within the XMANAI Manufacturing App and the flexibility of the XMANAI platform in configuring data pipelines and offering ML tools for a wide range of applications. Some important key learnings were collected that are very relevant for the next phase of the project and for the future exploitation of the XMANAI solution in the company. Firstly, the quality of the data pipeline is crucial to ensure the quality of the results: this seems to be trivial, but the companies realize the real quality of their data only when they start the challenge of predictive analytics and, in case it is proven poor, the cleansing activity may be long and complex. In addition, the companies often do have not, within their organizations, the competence and/or the accountability to manage the data pipeline, as the awareness of the importance of data management is still very immature. Finally, also the awareness of the users on what AI and XAI may offer in terms of opportunities and constraints is in general still very poor and polluted by the news and fake information available on social networks and the internet, which inflate expectations and fears.
Therefore, the right path for the completion of the XMANAI project and its successful deployment must act both on technical and organizational aspects in a holistic approach to the XAI technology introduction.

Key benefits are expected by the successful completion of the demonstrator both in terms of business results and of people knowledge maturation:
- Customer satisfaction
- Revenue’s opportunity maximization
- Tailored inventory strategy
- Promotional actions effectiveness
- Product range optimization


AI

# XMANAI PROJECT FACTSHEET

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RIA - Research and Innovation Action

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