Exploring LLMs and Semantic XAI for Industrial Robot Capabilities and Manufacturing Commonsense Knowledge*

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1. Context and Motivations

In the context of Industry 4.0, flexible manufacturing is especially essential for developing future factories with enhanced planning, scheduling, and control [1]. The quick and effective adaptation in the production line in response to customers' requirements or facing unwanted situations will considerably promote flexibility in manufacturing. For instance, due to the COVID-19 crisis[1], some companies have been re-purposing their production lines to join the fight against the pandemic[2] (e.g., perfumes to hand sanitizers and vehicles to ventilators). The question is how the human expert who runs the factory can know if the currently available resources (machines, tools, equipment, and technicians) can quickly and efficiently switch to a specific production process based on new work orders [2].

Similar disruptions may arise from extreme weather, longer-term climate change, declining international order, economic crises, changing societal priorities, cyber threats, or terrorism. Furthermore, flexibility in the manufacturing industries is more critical than ever to tackle ever-growing product variability, supply chain volatility, and unpredictability of customer requirements. Product life cycles are becoming more and more dynamic; also, at the same time, the number of product variants continues to grow. There is a need for more flexible, trustworthy, and efficient manufacturing processes.Traditional manufacturing paradigms such

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[1]https://www.weforum.org/agenda/2020/03/from-perfume-to-hand-sanitiser-tvs-to-face-masks-how-companies-are-changing-track-to-fight-covid-19/

[2]https://www.unido.org/news/covid-19-critical-supplies-manufacturing-repurposing-challenge

as lean manufacturing, just-in-time production, and KANBAN [3] systems often struggle to adapt to unforeseen disruptions. These systems can fall into a "rupture condition" when faced with unexpected challenges like pandemics, economic crises, or cyber threats. Rapid reconfiguration of operations highlights the need for flexibility in manufacturing to manage product variability, supply chain volatility, and unpredictability of customer demand.

Most production planning still depends on industry standards, best practices, manufacturing know-how, and machinists' experiential knowledge. Despite the advent of Artificial Intelligence (AI), industries still depend on human expertise to make process planning decisions in an unprecedented situation because of uncertain or low expectations of AI investments (Trust). Personal judgment overrides AI-based decision-making (Human-reasoning).

However, human experts will only trust and accept AI results if the automated decision-making process is transparent [3][4]. If the AI system decides that a production step or plan matches or does not match the capabilities of a particular machine, the human expert should understand why this decision is made (i.e., which of the machine's capabilities leads to such a decision). Accordingly, a trustworthy AI, commonly called explainable AI (XAI) [5], should be able to explain why a particular decision was reached in a way that human experts can understand, for example, in the case of real-time decision-making for manufacturing operations, why some processes were performed, what process is currently being performed, and what processes should occur in the future. However, the explainability of the AI model standalone is not enough; decision logic must also be transparent and grounded in interpretable knowledge structures to ensure accurate understanding, paving the way for integrating semantics alongside these models.
Semantics is the study of meaning [6]; it corresponds to providing structured and meaningful explanations that are not only data-driven but also align with real-world concepts. Ontologies are crucial to providing this semantic structure and adding context to the explanations. Ontologies are defined as an explicit formal semantic representation of knowledge through logical axioms [7].

The use of semantics in explaining various types of supervised and unsupervised learning models was presented by Seeliger et al. [8]. In a narrower scope, Bianchi et al. [9] reviewed methods of embedding knowledge graphs in ML models to achieve explainability. Regarding the quality of the explanations, past research in behavioral psychology [10][11] showed that three qualities make the explanations more intuitive for humans. Such explanations must be more straightforward in that they include fewer general reasons, mention well-known events as reasons, and be coherent and consistent with prior knowledge. This stresses the need to adopt XAI techniques that are not solely data-driven (statistical learning) but embed semantic-driven symbolic reasoning in the prediction models from the ground up. Research is scarce in this direction, with only a handful of other projects targeting XAI-based hybrid AI for manufacturing, such as AI4EU44[4]or XMANAI[5]. Humans expect explainable decisions based on what they consider commonsense (i.e., simple facts about people and everyday life, data evidence, and causal reasoning).

[3]https://leanmanufacturingtools.org/kanban/
[4]https://www.ai4europe.eu/
[5]https://ai4manufacturing.eu/

Commonsense knowledge (CSK) explanation is the most meaningful and sought-after explanation technique [12]. According to the state of the art, incorporating and implementing CSK capabilities into AI can enhance the overall manufacturing potential and accelerate the growth of AI applications in the industry [13]. However, representing CSK related to manufacturing is challenging [14]. In the literature, significant progress has been made in four areas related to CSK in AI, mainly reasoning about taxonomic categories, logic, time and space, and actions [15].

Yet, there seems to be no CSK for the industry that integrates all main aspects of manufacturing process requirements. The manufacturing commonsense knowledge (MACS) should cover generic manufacturing background knowledge that human experts, such as machinists, planners, and shopfloor managers, carry as part of their experience to know or assume to understand and reason about information (or situation) that they are dealing with (e.g., a machine needs some kind of energy, a machine can breakdown, the production process needs raw materials, etc.). Generating commonsense explanations requires integrating richer domain knowledge [16] represented through ontologies.

The ontologies should cover production-relevant domains, including machine capabilities, production process, product specifications, raw materials, etc.

We examine current methods for manufacturers to increase transparency in AI system decision-making as a state of the art methodology structure shown in Fig.1. Two promising areas of XAI are ontology-based (O-XAI) and semantic-based (S-XAI), which use semantic information to provide human-readable explanations of AI decisions. Translating AI algorithm decision paths to meaningful explanations using semantics, O-XAI, and S-XAI helps humans identify cross-cutting concerns influencing AI system decisions. We discuss the pros and cons of using O-XAI and S-XAI systems in manufacturing and future research potential to guide researchers and practitioners in utilizing these explainable systems for decision-making [18].

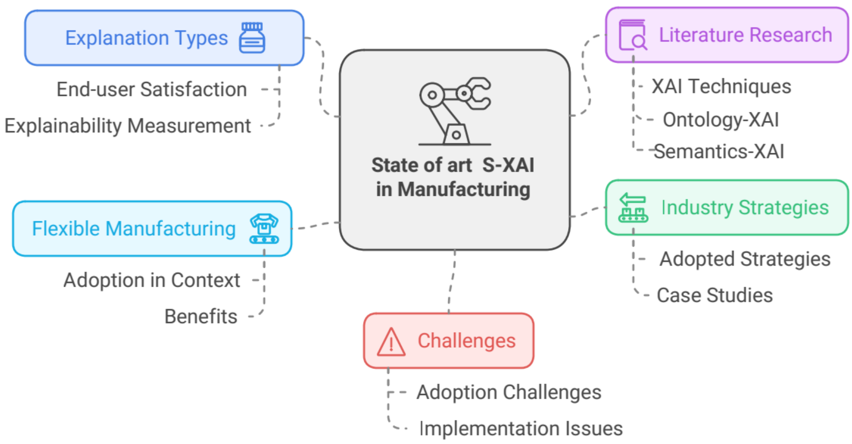

Figure 1: Semantics based XAI in manufacturing

"CSK and Hybrid AI for Trustful and flexible manufacturing 4.0" (Chaikmat 4.0)[6] is a research project funded by the French National Agency of Research ANR that aims to add flexibility and transparency to manufacturing through trustful automatic decision.

In the context of flexible manufacturing, the selection of resources must also consider the dynamically changing conditions of the shop floor, including factors such as the age of the machines, maintenance histories, and the availability of operators. These considerations are crucial to determining the actual performance of machines and equipment. CHAIKMAT's core objective is to evaluate whether available machines can execute specific production processes effectively.

The project seeks to add flexibility and transparency to manufacturing through reliable automatic decision-making systems. These systems are designed to provide human experts with meaningful explanations about decisions, using MACS to make the process clear and understandable. To meet these challenges, CHAIKMAT,s proposes a hybrid approach that bridges the gap between human expertise and AI-based decision-making. This strategy proposes efficient resource use and enhanced industrial flexibility, laying the groundwork for more advanced manufacturing operations [17].

2. Thesis Objectives

The primary objective of this thesis, within the scope of the project, is to investigate the use and effects of ontology-based models in manufacturing in the context of semantic reasoning, explainability, and efficient formalization of machine capabilities. The focus is primarily on robotics, with the intention of improving the explainability of how robots are assigned tasks based on their capabilities. This involves developing and validating ontological models to encapsulate MACS and robotics capabilities for decision-making and explainability. The following are the objectives that have been outlined below:

- Formalization of machine specifications that include capabilities, capacities, functions, quality, and process characteristics, focusing on robotics.
- Establish a framework for identifying MACS patterns, extracting MACS, formalizing MACS using standard vocabulary, converting them into semantic rules, and leveraging MACS patterns within decision-making processes.
- Utilization of machine capabilities and MACS patterns, alongside a neural network framework, to explain whether an existing set of machines can perform a specific task or not based on robot capabilities.

3. Research Questions

Developing methods for utilizing machine specifications and MACS patterns, along with integrating a semantics-based explainable AI (S-XAI) framework, is crucial to achieving the primary objectives of this thesis. These elements will enhance decision-making processes, increase user

[6] https://chaikmat-anr.uttop.fr

trust, and provide transparency. The following research questions have been formulated to guide this investigation:

- How can we formalize key notions such as Capability, Capacity, Function, Quality, and Process Characteristics in the context of robotics?
- How can MACS be extracted, formalized, and integrated into decision-making processes to enhance explainability?
- How can ontologies and knowledge graphs can facilitate the creation of explanations that align with human understanding while enhancing the use of S-XAI in manufacturing decision-making processes?

4. Contribution

This thesis presents three critical contributions to improving the explainability of the decision-making process in manufacturing by integrating robotics capabilities, MACS, and S-XAI.

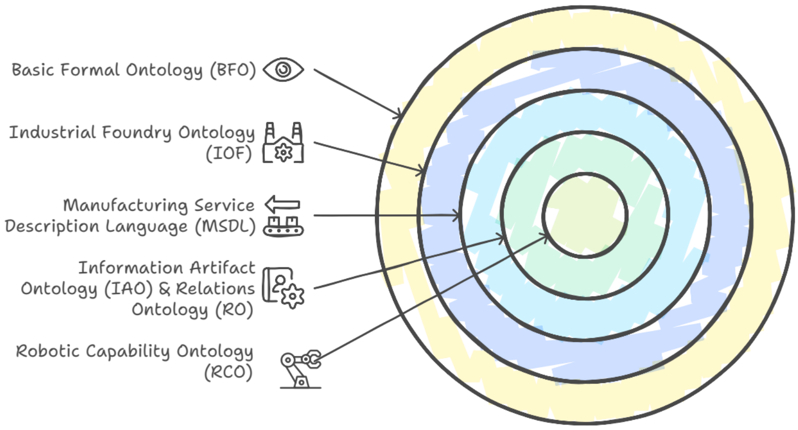

Figure 2: Robot Capability Ontology

Our first contribution is the development of the Robotic Capability Ontology (RCO) [19], an application ontology specifically designed to model robotic capabilities [19]. RCO utilizes the Manufacturing Service Description Language (MSDL) [20], a domain reference ontology created for manufacturing services and aligned with the Basic Formal Ontology (BFO) [21], Industrial ontology Foundry (IOF) [22], Information Artifact Ontology (IAO) [23], and Relations ontology (RO) [24] as shown in Fig,2. MSDL's modular structure and domain-neutral classes allow RCO to describe and expand upon robotic capabilities accurately. This enables the design of an ontological model that precisely captures robotic specifications from its specification manual as advertised capabilities to actual capabilities in an operational environment as operational capabilities.

Our second contribution introduces the concept of MACS. We propose a methodology for identifying MACS patterns, extracting, formalizing, and modeling this knowledge, and a standardized vocabulary that organizes MACS into semantic rules, as shown in Fig.3. These semantic

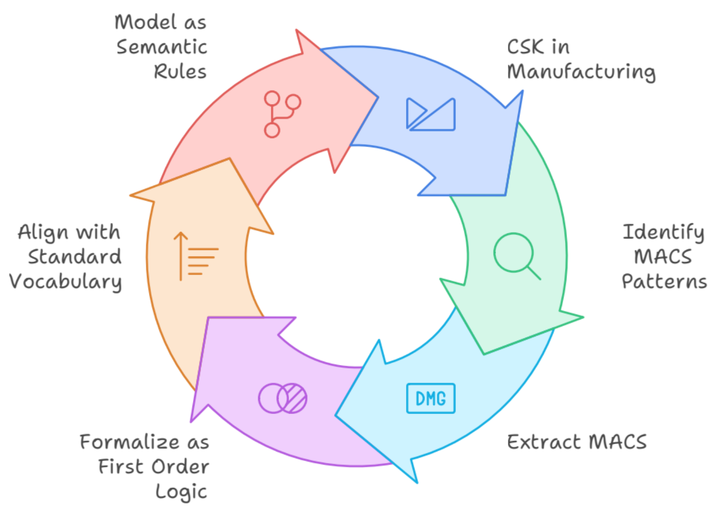

Figure 3: Manufacturing Commonsense Knowledge

rules are then converted into schema languages such as SPARQL and Datalog rules, which are used to create a MACS Knowledge Graph (MACS-KG) to demonstrate the applicability of the proposed method.

Our third contribution is developing a (S-XAI) framework as shown in Fig.4. that incorporates a neural network model trained on historical data about different tasks to predict robotic operational capabilities such as 'Repeatability' and 'Precision' on a given set of coordinates for a new task.

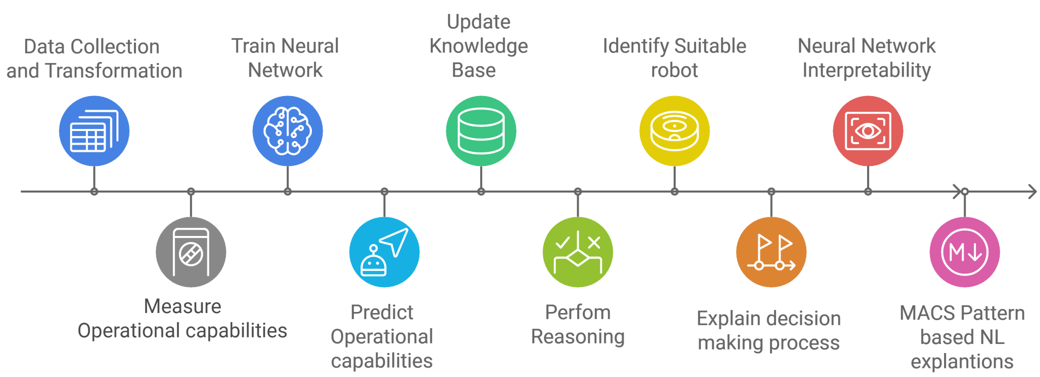

Figure 4: Semantic-XAI

Also, utilizing XAI techniques like Local Interpretable Model-Agnostic Explanations (LIME), Partial Dependency Plots (PDP), and Permutation Features Importance (PF) for the prediction of operational capabilities from neural networks alongside natural language explanations based on MACS patterns, the system provides clear, logical, and understandable explanations for each prediction.

5. Summary

We propose an S-XAI framework to address the concern about explainability issues related to the decision-making process in the manufacturing industry. The framework combines neural networks for predictive analysis of robot operational capabilities with rule-based reasoning grounded in MACS. This approach brings transparency and explainability to decision-making, ensuring stakeholders can trust and understand automated decisions.

A vital feature of the framework is the ability to integrate symbolic and sub-symbolic reasoning paradigms, enabling real-time, explainable decisions in manufacturing environments. By incorporating a neural network, the system will be scalable with the increasing data volume and continuously improve through active learning. At the same time, the use of manufacturing commonsense knowledge ensures that explanations provided to users are contextually relevant and easy to comprehend, fostering user trust and system acceptance.

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