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AI-enabled Enterprise Information Systems for Manufacturing

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Abstract: Research work presented in this paper considers the contemporary Enterprise Information Systems (EIS) functional architecture and carries out the literature review of AI applications integrated in Customer Relationship Management, Supply Chain Management, Inventory and logistics, Production Planning and Scheduling, Finance and accounting, Product Lifecycle Management and Human Resources, with special attention to the manufacturing enterprises. As a review outcome, the enhanced capabilities are identified in each of those processes and proposed as AI services. AI-enablement is related to the capabilities of the enterprise to implement improved decision making or automation by using (a) Machine Learning (ML) models or (b) logic-based systems. It is a process of the enterprise transformation leading to the convergence of the 4 major disruptive technologies, namely Industrial Internet of Things (or Cyber-Physical Systems), Agent-based Distributed Systems, Cloud Computing and Artificial Intelligence (non-symbolic AI like Machine Learning, Neural Networks; symbolic AI like Reasoning and Logic/Model-based AI).

Keywords: Enterprise Information System, Artificial Intelligence, Machine Learning, Formal Logic Reasoning, Cyber-Physical Systems, Agent-Based Systems

Introduction

Capacity and capability to adapt have become a key factor of competitiveness in the industry today. It can be considered on both micro and macro levels, and it encompasses a range of circumstances, from the optimal operational response to handling disturbances at the shop floor level, to making business decisions in response to the changing market trends.

To some extent, the capacity to adapt is related to access to relevant data, owned by the enterprise or from external providers, while capability corresponds to the enterprise ability and skills to effectively interpret, understand, and process these data and make best-informed

decisions on the industry's operations and market environment trends. The former (capacity to adapt) is/will be achieved in so-called sensing enterprise, the enterprise which continuously listens to its internal and external environment, by using the technologies such as sensors, embedded electronics, and multi-agent systems. The paradigms of Cyber-Physical Systems and Internet of Things are considered as critical enablers for the sensing enterprise development strategies. The latter (capability to adapt) is related to making sense of all this data, and it is expected to be achieved in the so-called AI-enabled (smart) enterprise (cf. Smart, Sensing and Sustainable (S³) Enterprise (Weichhart et al., 2016)).

The so-called Enterprise Information Systems (EIS) - the parameterizable software applications dealing with the partial or the complete management of an enterprise resources, processes or information - aim to solve common problems, such as lack of process automation, flexibility, responsiveness, scalability, traceability, coherency and integration in as less as possible intrusive ways. However, they often fail to address those issues consistently and the typical reason for that is the complexity of the process of EIS development and/or implementation in which different and diverse stakeholders fail to effectively communicate around the business objectives and key factors for their achievement. Complexity is multiplied with the factor of the long duration of the software development life-cycle in which those objectives could easily become legacy. A solution to this problem is the Model-Driven Engineering (MDE) which facilitates near real-time system customization and efficient response to a change. MDE relies on the human perceptions of the realities of the enterprise, which are sometimes incomplete or inaccurate. Data-driven approaches address this challenge by embedding machine-learned understanding of the enterprise realities represented by raw data, into the respective models.

Increased access to data and improved computational power, provided by the modern EIS infrastructures, made it feasible to use the stack of so-called Artificial Intelligence (AI) tools,

methods and algorithms both in data acquisition and processing, directly related to capacity and capability to adapt, respectively. Modern enterprise is lean and digital (Deuse et al., 2020). Its AI-enablement occurs when it becomes capable to implement improved decision making or automation by using Machine Learning (ML) models or logic-based systems, while exploiting vast, diverse channels enabling data access. In a bottom line, the AI-enablement will facilitate the autonomous acting and decision-making processes, and achievement of so-called self-* properties, such as self-configuration and self-healing (Sanchez et al., 2020).

The first objective of the work behind this paper is to analyse and systematise the existing body of evidence on the scope and maturity of the technologies which facilitate AI-enabled EIS, where both may be considered at the levels of development, implementation, and integration with existing EIS. Technologies that are commonly known as parts of the AI stack are Machine Learning (including Deep Learning), Natural Language Processing (NLP) and knowledge representation and reasoning. Such evidence is presented as the result of the exhaustive literature review. The review will consider the specific EIS functions, namely: Customer Relationship Management, Supply Chain Management, Inventory and logistics, Production Planning and Scheduling, Finance and accounting, Product Lifecycle Management and Human Resources, identified as especially important in the manufacturing enterprises. The review will not deal with the non-functional aspects of EIS, such as security, human-computer interaction, performance, accessibility, scalability, and others.

The second objective is to perform synthesis that aims at identifying the specific AI services in the defined scope, described by the EIS functions listed above. The purpose of this synthesis is to highlight the trends, opportunities and challenges for AI-enablement of the EIS, not to be used as a working architecture model. Finally, ad hoc exercise of the possible impact identification is carried out, with co-authors as the participants.

The structure of this paper follows the line of thought implied above. First, in the background section, we introduce the reader to the functional organization of the EIS. Introduction to the Machine Learning and Logic-based methods is provided, explaining the key terms and concepts behind those two major domains and highlighting the differences between data-driven and formal logic driven support to decision making. Then, in the literature review section, the most prominent findings in each of the EIS functions are presented. Finally, based on those findings, AI services of the AI-enabled enterprise and respective data requirements are identified and presented.

Background

In this section, we first discuss the basic applications of EIS and the functionality they provide. This is followed by a discussion of technology drivers for modern EIS. The final part of this section introduces the reader to what is today referred as Artificial Intelligence. We consider two general approaches: non-symbolic AI (e.g., Machine Learning, aka. sub-symbolic AI) and symbolic AI (e.g., knowledge-based systems, ontologies, knowledge inference).

EIS Functions

For the EIS functions we will discuss, we have chosen the most relevant ones for the manufacturing (based on our experience). The distinction between functions is often blurry and will be realised in different concrete implementations in different functional packages. For example, planning of human resources based on skills for production will be found with Enterprise Resource Planning (ERP) systems and with Human Resources (HR) information systems. Nevertheless, we will use these functions to structure the discussion.

The following figure shows the functions which address internal (here Human Resources Management (HRM), Finance (FIN), Product Lifecycle Management (PLM), Enterprise

Resource Planning (ERP), Advanced Planning and Scheduling (APS), Logistics & Inventory (LOG&Inv), and external components (Customer Relationship Management (CRM), Sales, Supply Chain Management (SCM) of EIS infrastructures. Fig. 1 presents the functions in different groups. A brief discussion on the individual function is given in the table that follows.

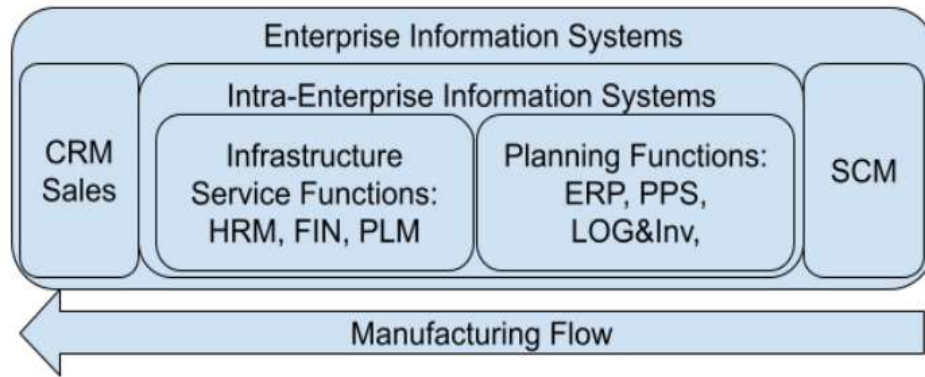


Fig. 1. EIS functions.

Table 1: Different Enterprise Information Functions

Name	Description of Function
Supply Chain Management	SCM helps to manage inward flows of a company.
Enterprise Resource Planning	ERP facilitates planning of required resources in terms of (raw) materials, parts, human operators, for operation of the enterprise.
Advanced Planning and Scheduling	Planning includes coming up with an answer to the question ‘what to produce today (next week, ...)’. Scheduling comes up with the next level of detailed question of ‘when to produce’ the parts that planning has proposed to do. This includes fine granular sequencing of production steps on different machines.
Logistics & Inventory	Inventory and logistics function deal with how the raw materials, parts, assemblies, and finished products are stored, moved from one to another location, organized in routes and transported from and to the supplier and customer locations.
Finance and Accounting	Finance and accounting address the problem of financial data management.
Human Resource Management	Human Resource Management function provides information related to the time management, skill management of employees.

Product Lifecycle Management	PLM systems help to manage information related to product-related knowledge, data, and processes for innovation, development, maintenance, and retirement.
Customer Relationship Management (including Sales)	Customer Relationship Management (CRM) is a process of managing interactions with existing, past, and potential customers.

In general, there is a huge set of methods contributing to AI research (Melanie Mitchell, 2019). The two categories (symbolic, sub-symbolic AI) distinguish between two general different approaches towards reaching human-like intelligence with machines.

In symbolic AI, the instructions for the machine are encoded using signifiers (Representamen) that makes sense to humans (Interpretant) and eventually point to certain real-world artefacts (referents, objects). The approaches of symbolic AI try to support encoding human thought processes. Here, person(s) providing facts and rules also provide the semantics of the model (Chandler, 2007). Early AI applications of this category include expert systems, ontologies, multi agent systems (Melanie Mitchell, 2019). Symbolic AI is grounded in mathematical logics.

The sub-symbolic category consists of approaches where the algorithms do not contain such symbols but work with numbers - data. One of the key inspirations for the development of this area were artificial neurons. An artificial neuron mimics the signal processing of the brain neurons. Here, multiple inputs (dendrites) are aggregated in the cell body and passed to an axon (output). Without going into details of the biological signal processing (function) in the cell, artificial neural networks bring together many such artificial neurons. All neurons are connected with neurons from lower and higher layers. Recent hardware developments in processing power of CPUs and GPUs now allow artificial neural networks with many layers enabling what is now called deep learning (Melanie Mitchell, 2019). The weights between the

neurons need to be trained (there are no symbols that can be manipulated). That is done using (typically huge amounts of) data.

Artificial Intelligence Methods

Machine Learning Methods

Machine Learning (ML) is the study of approaches and algorithms to solve different classes of prediction or decision problems (that cannot be effectively solved analytically or programmatically) in the domains described by experience, where this experience, represented by data is used to automatically improve the effectiveness of those solutions (adapted from Mitchell, 1997). Traditionally, ML approaches and applications are divided into three categories: supervised, unsupervised and reinforcement learning.

In supervised learning, a selected algorithm learns from the existing data to map the selected input into the selected output. For example, for the particular machine tool, historical data on the power consumption, vibrations, temperatures in the work area (input data) can be mapped to a time to failure (continual output data), and thus used for predicting the exact time of failure (Carvalho et al., 2019). In supervised learning, output data is often classified using labels, associated to each of the individual sets of input data by a human, typically an expert. For example, the ML algorithm can be trained to distinguish between normal and faulty behaviour by learning from the large set of recorded sounds, each of which was associated with one of the labels - nominal output features (normal, fault), where those associations were made by the expert (Yao et al., 2018). There are many different algorithms, broadly divided into the classification and regression algorithms, depending on whether the output feature is a nominal or continual one, respectively. The most commonly used traditional supervised learning algorithms are Naive Bayes, linear and logistic regression, Decision Trees and Support Vector Machine (SVM) (Cortes & Vapnik, 1995). Ensemble methods (Opitz & Maclin, 1999) combine

multiple algorithms to improve the prediction performance. Random Forest (Tin Kam Ho, 1995) and Gradient Boosting (Breiman, 1997) are today considered as the most effective traditional ML algorithms.

Unsupervised learning is used to discover meaningful patterns or structures in the existing data. Clustering, namely grouping of data instances of some similar characteristics is one of the most frequent problems addressed by unsupervised learning algorithms. For example, it can be used to group the suppliers, based on their production capabilities (Sabbagh & Ameri, 2018). The most commonly used traditional algorithms for clustering are k-means clustering (MacQueen, 1967) and k-nearest neighbours (Altman, 1992). Anomaly detection (Zimek & Schubert, 2017) is another class of problems that are typically addressed by some unsupervised learning approach. It is the identification of occurrences or values, significantly differing from the vast majority of data. It is often used as a main technique for detection of manufacturing components faults (C.-Y. Chen et al., 2020).

Reinforcement learning (RL) agents carry out a sequence of decisions with limited feedback, where each of those is made on a trial-and-error basis, penalized, or rewarded (based on a given reward policy). The objective of the agent is then to maximize the reward and, in this path, learn to implement very sophisticated successful tactics in resolving some specific problem, after starting from totally random trials. Basic reinforcement is modelled as Markov decision process (Bellman, 1957). In manufacturing, RL is often used for autonomous robotic operation (Oloff et al., 2020). One of the most popular techniques for implementing RL agents today is Q-learning (Watkins & Dayan, 1992).

The development of Artificial Neural Networks (ANN) and especially new deep learning architectures, such as convolutional (LeCun & Bengio, 1998), recurrent (Rumelhart & McClelland, 1987) and attention-based neural networks (Vaswani et al., 2017) are probably the most significant drivers for innovative and practical application of ML for addressing each of

the groups of problems listed above. Convolutional Neural Networks (CNN) effectively implement a feature engineering method to reduce the complexity of very large datasets (such as images). They are most often used for addressing computer vision problems such as image classification, object localization, classification and segmentation. In manufacturing, they are being used for quality control/part inspection, process understanding and monitoring many aspects of the operations through interpretation of camera signals (Noble, 1995). Encoder-Decoder neural networks, namely the Recurrent Neural Networks (RNN) and Long short-term memory architectures - LSTM (Hochreiter & Schmidhuber, 1997) are designed to address the problems related to sequential datasets, such as time-series, natural language, speech, and videos. In a nutshell, both RNN and LSTMs maintain a single so-called hidden state vector which stores the context of the entire sequence of data. The examples of sequential data in the industrial domains that can be forecasted by using the above models are numerous: historical sales and demand data, manufacturing schedules, machine vibration and noise, and others. Accurate sales and demand forecasts can significantly reduce costs and increase profits of the manufacturing enterprises. Forecasting is a critical competitive strength of the enterprises striving towards mass customization (M. Kim et al., 2019).

In ML, Transfer Learning (Olivas et al., 2010) is an approach which assumes that the model trained with some specific dataset describing the particular domain, can be effectively used for making the predictions in a different but somewhat similar domain, demonstrating the power of ML algorithms to generalize beyond what is used to explicitly learn them. For example, upper layers (e.g. classification layer) of the pre-trained CNN can be re-trained with new image data, to combine power to recognize and interpret low-level features (e.g. lines, shapes, etc.) with a power to detect particular objects on images (Shin et al., 2016).

As the use of AI algorithms and approaches increase, the issue of the right to understand the effect of the decisions made by AI-enabled EIS will emerge. Growing concern on potential

bias in AI models and a demand for model transparency and interpretability is addressed by the Explainable AI (XAI) stack of methods and approaches (Gilpin et al., 2019). XAI helps to highlight evidence that the prediction model is trustworthy, that it is not biased, or that is compliant with regulation. It typically refers to post-modelling explainability of pre-developed models. Global explainability refers to discovering the features' importance while looking at the whole model (trained with all available data). Local explainability relates to facilitating understanding of how input data is used by a model to make a prediction or a forecast for an instance of a class.. Some of the most commonly used approaches to local explanation are Local Interpretable Model-agnostic Explanations (LIME) (Ribeiro et al., 2016) and SHAP (SHapley Additive exPlanations) (Lundberg & Lee, 2017). Model explainability is a prerequisite for building trust and facilitating adoption in the areas which are characterized by high privacy, reliability and safety requirements, as well as those where AI-facilitated decisions have significant socio-economic implications, such as recruitment, energy management, accounting, strategic planning, predictive maintenance, automated transportation and others (Gade et al., 2019).

Logic-based Methods

Early AI approaches have been relying on models (i.e. facts and rules) engineered by humans. Several languages have been researched to capture logic for different use cases.

One of the first logic programming languages was PROLOG. It builds on formal first-order logic, and is a declarative programming language. A deductive logic system consists of a set of inference rules and logical axioms that determine which sequences of formulas constitute valid proofs (Lloyd, 2012). The human engineer provides facts and rules, the inference mechanism is then used to deductively reason if a certain statement (i.e., query) is true. As such, logic-based approaches are model-driven systems.

In general, the possibility to model the behaviour of intelligent agents is of great importance for reasoning over enterprise functions. An agent is an intelligent system that senses its environment and can act autonomously within it. In the research domain of Distributed Artificial Intelligence multiple intelligent agents are interacting and communicating (M. Wooldridge, 2009; M. J. Wooldridge & Jennings, 1995).

To be able to act intelligently, agents in Multi-Agent-Systems (MAS) have the capability to follow their goals and make plans based on beliefs they have about their world. The capability of sensing and adapting the behaviour and the ability to cooperate with other agents, allows to build systems that are Complex Adaptive Systems (CAS) (Holland, 1996, 1998). The capability to handle adaptive behaviour is also important for interoperability of enterprise information systems (Weichhart, 2014).

A logic-based approach to dynamic systems is the situation calculus (J. McCarthy & Hayes, 1969). This is a formal approach that supports reasoning about actions and change. The approach supports reasoning about behaviour and the consequences of enacting a behaviour (Reiter, 2001). The situation calculus builds on first-order logic and has elements of second order logic. This can lead to computational complex reasoning.

An interpreter, named GOLOG, exists that builds on the situation calculus and a theory of action (Levesque et al., 1997). It aims at 'high-level control of robots and mechanical devices, programming intelligent software agents, modelling and simulation of discrete event systems, etc' (Levesque et al., 1997, p. 60). A prototypic implementation of GOLOG exists in PROLOG. Some attempts have been made to provide a GOLOG interpreter that runs on embedded systems and an extension for agents and robots has also been researched (Ferrein et al., 2012).

A different formal approach to describe behaviours is the Abstract State Machine (ASM) (Fleischmann et al., 2012). ASM has been used to implement an interpreter for processes

modelled in subject-oriented business process modelling language (Lerchner & Stary, 2014). S-BPM has also been used to model behaviour (and processes) of cyber-physical systems (CPS) (Weichhart et al., 2020). This is important for process-oriented information systems that are capable of handling the dynamics of enterprise systems (Weichhart, 2020; Weichhart et al., 2016).

A general approach to (human-like) reasoning are cognitive architectures (A. Newell, 1990). Cognitive architectures aim at research in general AI - and implement human-like reasoning mechanisms. The goal is to understand how humans think, by providing a formalism (the architecture) which allows mimicking human thinking. Programs written using cognitive architectures (in their final version) would be able to reason across many domains and adapt to new situations and are able to reflect on themselves. Cognitive architecture research supports cognitive science by providing detailed (executable models) of human 'thinking' processes (A. Newell, 1990).

Cognitive architectures can be distinguished between three types: (i) symbolic (also referred to as cognitivist), (ii) emergent (connectionist) and (iii) hybrid (Kotseruba & Tsotsos, 2018). In type (i) systems, concepts are represented using symbols that can be manipulated using rules (see logic-based approaches in general). These systems have the advantage to be understood by humans and are good at planning and reasoning. Type (ii) systems aim at adaptability and learning by using massively parallel models (e.g., artificial neural networks) where information propagates as signals between neurons. The third type combines both strategies to get the best of both worlds (Kotseruba & Tsotsos, 2018).

Cognitive architectures are also linked to physical realisation of the symbols that are manipulated (Allen Newell, 1980). The idea of 'Physical Symbol System', is to create a system that is capable of having and manipulating symbols, which can also be physical.

‘The notion of symbol that it defines is internal to this concept of a system. Thus, it is a hypothesis that these symbols are in fact the same symbols that we humans have and use every day of our lives. Stated another way, the hypothesis is that humans are instances of physical symbol systems, and, by virtue of this, the mind enters into the physical universe. In my own view this hypothesis sets the terms on which we search for a scientific theory of mind. What we all seek are the further specifications of physical symbol systems that constitute the human mind or that constitute systems of powerful and efficient intelligence.’ (Allen Newell, 1980, p. 136).

Cognitive computing is also highly relevant for enterprise information systems, in particular in big data analytics contexts (Khanra et al., 2020; Sangaiah et al., 2020; Dai et al., 2020).

It has to be noted that Multi-Agent Systems (MAS) have also been linked to physical agents early on. The first standard for MAS has been created under the umbrella of FIPA - Foundation of Intelligent Physical Agents¹. Recently, the view that physical systems are integrated in the reasoning and virtual world resulted in the notion of Cyber-Physical Systems (CPS). The concept of CPS has multiple roots. One is in embedded systems research, where the CPS is a system that integrates hardware and software (Monostori et al., 2016). In this view, the CPS is a single system with tightly coupled hardware and software; networking capabilities are common but optional. A different root is the convergence of physical manufacturing systems and IT systems (cyber-systems) forming Cyber-Physical Production Systems (CPPS) (Weichhart et al. 2021). This takes a system-of-systems point of view with mandatory networking between systems. A basis for this are holonic manufacturing systems (Valckenaers, 2019) and multi-agent systems for production (Monostori et al., 2016). CPPS are formed through connected CPS that communicate using edge computing, fog computing, and cloud

¹ <http://fipa.org/>

computing. The connectivity and distribution support computationally intense reasoning and learning in cloud systems, and real-time reactivity using edge systems (Panetto et al., 2019). In any case a CP(P)S requires sensors to connect to the physical environment; the sensed information is transmitted to the decision-making computational system and (semi-) automatic decisions are used to control actuators which realise their effect in the physical world.

Cyber-Physical (Production) Systems provide a rich and challenging environment for the application of Artificial Intelligence. These systems are agnostic to the kind of AI. Sub-symbolic approaches offer many possibilities in the sensing part of the CPS (e.g., sensor values classified). Symbolic approaches like MAS provide a collective view on CPS where multiple such systems are connected and are interacting.

The sensing enterprise and the S³ Enterprise (sensing, smart and sustainable) enterprise (Weichhart et al. 2016 & Weichhart et al 2021) is a particular approach that shows the potential of combining symbolic and sub-symbolic approaches. Using a distributed architecture, based on multi agent systems, a single agent can be assigned to classify the data it is sensing by using a sub-symbolic AI approach. That class would be assigned a label (name) which is then used to communicate a certain state to the other agents. Such approaches allow to build agents that use hard-coded statistic approaches for determining labels and can be used on raw data without prior learning. The multi agent system approach also allows to build virtual sensors integrated in agents. A virtual sensor is predicting a sensor value by looking at other data. It is deriving an output value through indirect observation. With adding a virtual sensor agent to an agent that is directly observing this value, it becomes possible to train the virtual sensor agent first. After the training phase, it is possible to compare the virtual agent's output and the sensor agent output. If both values differ by a high margin, then it's possible to conclude that there is (a) an exceptional situation where the prediction fails or (b) the sensor value is wrong.

The systems with the above-described capabilities are capable to be remotely deployed on IIoT (Industrial Internet of Things), Edge, Cloud Computing devices. Also, by having local intelligence (classification), the amount of data is reduced and the speed of communicating a fact is increased. Agents in the cloud can use the communicated facts (without the need to consume the raw data stream) to make decisions. Such cloud-situated agents can use logic-based and reasoning for automated decision making and/or provide visualisation to humans. The human or agent-based decisions can then be communicated to robotic agents (in the general sense) that execute the decisions by transferring communicated objects into physical analogue actions.

This above example also illustrates the loose coupling a multi agent systems architecture provides. For semantic interoperability of the agents, a common ontology can be used to encode the messages' content. The developers of the agents in the system agreed to that ontology. This allows to replace agents and / or the attached sensors, since the interface is well known and explicitly documented (in the ontology). Still, care has to be taken that the communication objects remain consistent between old/new agent (e.g. similar scales to measure a value). This approach allows to represent human-decisions using agents which communicate the decisions to other agents in the system. Yet, this approach does not guarantee that the right sub-symbolic approach is taken with respect to classifying raw sensor data.

Literature Review

The objective of this structured literature review is to identify enhancements of existing or innovative data processing and acquisition functionalities of EIS, realized by using some AI approach or techniques in data acquisition (e.g., data mining or acquisition by using some CPS infrastructure). Such functionalities enhance the existing EIS with AI-enabled or sensing

capabilities. In the synthesis of this review, those new capabilities will be used to identify the elements of the innovative AI-enabled EIS functional architecture.

The scope of this review does not include non-functional aspects of EIS, such as security, human-computer interaction, performance, accessibility, scalability, and others.

The search for the literature is performed at the intersections of the relevant AI technologies and EIS functions. The following AI technologies, related to different problems were used for constructing search criteria: supervised learning (forecasting, classification, regression), anomaly detection, reinforcement learning and explainability/interpretability.

Customer Relationship Management and Sales

Marketing and sales are today perceived and considered as intertwined processes, sometimes called a sales pipeline, in which the leads are created and discovered, relationships are matured through interaction between the potential customer and a sales agent, towards quotations and closures, actual sales orders.

Lead creation and discovery is a process in which the targets, feedback, and response to the particular (marketing) activities are very difficult to perceive. It is often implied and/or hidden in big data, making it a playground for AI-based approaches and methods. This data is everywhere and accessible through the company's e-commerce platforms. For example, web user profiling can be carried out based on server access logs data (Nasraoui et al., 2002). Classification models are often used to facilitate segmentation of the specific customer profiles (Florez-Lopez & Ramon-Jeronimo, 2009). For unknown customers (potential customers), classification models are used to identify leads and opportunities (Emtiyaz & Keyvanpour, 2012). XAI techniques can be used to provide detailed explanations for each of the identified opportunities and thus justify the investment in acquiring the specific client (Petersen & Daramola, 2020). Regression models are used to predict the customer profitability rate, based

on the specific profile (Florez-Lopez & Ramon-Jeronimo, 2009). Intelligent software agents, or chatbots can be used for automating social media promotion. Twitter and Facebook are used for acquisition of valuable data for training bots, including both communication constructs and affirmation of their influence (through engaging interactions, likes, shares, replies and impressions). LSTMs are used for building a bot to generate topical tweets and replies to tweets (Çetinkaya et al., 2020).

Communication with the customer can reveal quite important information related to the product design and improvement. Customer services typically maintain the database of all customer communications. In those, customers express complaints, their opinions about the product but also communicate the requirements for the future product generations. Machine learning and in specific anomaly detection approach can be used to extract unusual responses, for example with rare, but significant customer requirements (Seo et al., 2020). Much of a product satisfaction assessment is based on online ratings provided on major e-commerce platforms or specialized social media. Anomaly detection method can be used to discard the rates that do not correspond to the typical customer behavior, for example, attacks, competitor bots, etc (Günemann et al., 2014).

In the opposite direction, AI can be used to improve customer experience in product search. Searchable online platforms are today key resources for product placement and discovery by the customers. One of the key issues of those platforms is lack of user understanding on why product search engines retrieve certain items for them, contributing to imperfect user experience. This issue can be solved by using explainable retrieval models (Ai et al., 2020).

Besides obvious benefits in automation of time-consuming custom relationship building tasks, AI can be implemented to facilitate important decisions related to choosing the most effective and efficient activities for particular leads or for addressing customer churn. ML is used to predict the propensity of the closure of the individual sales leads. Those predictions can be used

to carry out an optimal amount of customer interactions, associated with the individual leads (Yan et al., 2015). Probabilistic classifiers are trained to rank initial leads based on their probability of conversion to a sales opportunity, probability of successful sale, and/or expected revenue (Duncan & Elkan, 2015). Data mining models, based on ANN are used to predict the behaviour of customers to enhance the decision-making processes for retaining valued customers (Bahari & Elayidom, 2015). Boosted SVM-based models have been proven very effective for predicting customer churn in the telecommunications industry (Vafeiadis et al., 2015). Then, those predictions can be used to increase customer retention, by designing targeted marketing plans and service offers (Sabbeh, 2018).

AI takes important roles in direct sales, through automating the communication with the customer, cross-sale and up-sale offerings and dynamic pricing. Machine learning and Natural Language Processing have been used for automating the direct sales, by facilitating implementation of sales chatbots. It has been found that sales 'chatbots are four times more productive than novice sales staff, and their ability reaches that of specialized consumer shopping employees' (Luo et al., 2019). Their performance can be significantly improved, as the bots can be better than humans in personalizing the communication with the customer, by detecting his/her personality and adapting to it (Shumanov & Johnson, 2020). Based on product data and past customer interactions history, ML can be used to classify a product to upsell or cross-sale to a specified customer account (Zeng et al., 2016). Specifically, a hybrid classifier integrating Logistic Regression and Adaboost ensemble algorithm is used to score the propensity of a credit card customer to take up a home loan with a finance company (Qiu et al., 2008). Recommender systems based on two-stage ANN generating product recommendations and inferring those recommendations that maximize the Customer Lifetime Value can be used as a generative model to explore different cross-sell scenarios (Desirena et al., 2019). Finally, Reinforcement Learning models are proven to be useful in cross-selling pattern discovery (N.

Li & Abe, 2011). Dynamic pricing is the dynamic adjustment of prices to consumers depending upon the value these customers attribute to a product or service. Recent research has shown that the prices will have to be adjusted in fairly sophisticated ways, based on sound mathematical models. In e-commerce, visit and visitor attributes, purchase history, web data, and context understanding can be used to predict the price of purchase for a particular classified customer segment (Gupta & Pathak, 2014). There are other approaches using ML for personalized dynamic pricing (Ban & Keskin, 2017). Besides traditional inventory-based models and auctions, RL approaches are used in e-commerce to compute the right price (Narahari et al., 2005). They are especially useful in multi-agent economies, consisting of buyers and competing sellers, where each seller has limited information about its competitors' prices (Dasgupta & Das, 2000).

One of the most common uses of AI in sales is related to forecasting. LSTMs are combined with ensemble methods, such as lightGBM to implement sales forecasting strategies for supply chains (Weng et al., 2019). Typically, LSTM performance is very dependent on the amount of data available for training. In the cases where this amount is insufficient, transfer machine learning based on additive regression models can be used to improve the forecasting accuracy (Hirt et al., 2020). Anomalies in time series data often occur, due to human error in data collection and processing, spikes due to the effect of the feature, which is not included in the model, etc. Forecasting accuracies are generally higher if those anomalies are identified (Tran et al., 2019) and removed from data before training the forecasting algorithm, such as LSTM. In contrast to wholesale, retail sale is less certain, it depends on many exogenous features (other than historical data) and thus it is mostly considered as a multivariate time-series forecasting problem and typically addressed by using LSTM-based models (Guo et al., 2013). Some of the often-used features in multivariate retail sales forecasting are meteorological data (X. Liu & Ichise, 2017). Besides using historical data, retail sales and demand are also forecasted by

analysing Google Trends (Boone et al., 2018). There are existing approaches for explainable multivariate time-series forecasting (Hsieh et al., 2020). Besides sales, other dynamic parameters affecting the sales that change in time can be forecasted as well. Non-linear non-parametric ML methods are used to forecast the consumer credit ratings by combining customer transactions and credit bureau data (Khandani et al., 2010). The time of sales closure for service organizations is forecasted (Megahed et al., 2016).

The concept of intelligent sales deals with integrated view to customer and product data, responsive customer care, automation and streamlined delivery. While they significantly increase the sales performance, it is still very important to surface ethical considerations around training data and use of AI outputs in practice. The discourses of fairness, accountability and transparency are very important for assessing the overall impact of intelligent sales (Wolf, Christine T., 2020).

Supply Chain Management

In meeting end customer demand, supply chain context assumes the complex network (most often hierarchical) of organizations, formed dynamically in a response to a business opportunity or as a result of a long-term collaboration. Supply Chain Management (SCM) is related to managing the flow of goods and services upstream or downstream in the supply chain. The application of AI methods in tools in supply chain context are considered in two aspects; first one is related to the formation, demand forecasting and other non-operational issues, while another addresses execution issues.

Bullwhip effect refers to large inventory variations in response to small changes in consumer demand as one move further up the supply chain. This negative effect is addressed by accurate supply chain demand forecasting. This is somewhat different from predicting the customer demand as the former is not always directly correlated to the latter. Communication patterns

between participants that emerge in a supply chain tend to distort the original consumer's demand and create high levels of noise. Distortion and noise negatively impact the forecast quality of the participants (Management Association, 2012). The forecasting models based on RNN and SVM architectures have shown the best performance in the early days (Carbonneau et al., 2008). In more recent approaches, the Gradient Boosting ensemble method has proven to achieve 89% accuracy score for predicting the next month purchase on the test dataset, based on a dataset with 10000 customers and 200000 purchases (Martínez et al., 2020).

In the era of mass customization, adaptive or dynamic configuration of supply chains, now enabled by more responsive and more flexible EIS is increasingly receiving focus from the scientists and practitioners. ML is used for automatic formation of the supply chain for the given incoming orders and the constraints from suppliers upstream (Piramuthu, 2005). Different fuzzy methods are used to solve supplier selection problems (Petrović et al., 2019). One example of the clear need for efficient and fast supply chain formation are emergency events. Supply chain collaboration is critical in a response to emergency events. Sometimes, such collaboration needs to deal with non-cooperative behaviour. Reinforcement learning is proven effective in setting up collaboration consensus with scenarios learning algorithms (Xiang, 2020). Once the supply chain is formed, its sustainability largely depends on the trust, collaboration and information sharing between its actors. Obviously, the data on above is very difficult to acquire in order to assess it. One innovative approach to solving this problem is social media content analysis in the supply chain context. It has been shown that the level of trust, collaboration and information sharing among the members of the supply chain can be determined by the sentiment analysis of the social media content published by the members (Swain & Cao, 2019).

Supplier grouping is important both for supply chain formation and different performance analytics. Different data and text mining approaches are used to discover non-trivial data

related to the production capabilities of suppliers. Then, K-means clustering and Topic Modelling approaches are used to cluster the suppliers (Sabbagh & Ameri, 2018). In agent-based supply chain networks, ANN models (separately for supply, production and delivery) are used to match actual customer requirements and agents' goals and constraints to facilitate complete order fulfilment across the entire supply chain, with significantly increased resource utilization (Chiu & Lin, 2004). Before the actual launch, RL algorithm can be used for assessment of whether the customer order to a supply chain should be accepted, based on the order delivery due date, the job price, the timeout penalty cost, and the information about the current plan and schedule of the supply chain (Stockheim et al., 2003).

In the execution context, AI technologies found the application in ordering management, dynamic pricing, and uncertainty management. Traditional ordering policies are time or event-triggered, being very easy to implement. However, in the dynamic supply chains, they often lead to excessive inventory or shortage. Supply chain ordering management can be considered as a multi-agent system and formulated as a reinforcement learning (RL) model (Chaharsooghi et al., 2008). The RL approach has been proven very effective in supply chains with high levels of uncertainty of customer demand, as it makes possible to have the control parameters designed to adaptively change as customer-demand patterns change (C. O. Kim et al., 2005). Order management is not the only process that spans the whole supply chain, in terms of management and control; ML can help to effectively optimize the energy consumption in supply chains, namely its actors, thus contributing to the better supply chain cost efficiency, its sustainability but also circular economy goals (D. Wang & Zhang, 2020).

The ability of the organization to accurately predict selling prices at a given time is especially important in the context of supply chain, for different reasons, including the specific contractual relationships, established collaboration, etc. The models based on ANNs, with associated

configuration settings and data pre-processing strategies are proposed for making price forecasts in a supply chain (Fasli & Kovalchuk, 2011).

Supply chain risk mitigation often depends on fast decisions made on large, multidimensional datasets, making it a suitable problem for addressing by using ML approaches (Baryannis, Validi, et al., 2019). The occurrence of supply chain disruptions, namely delivery delays can be predicted by using AI models, by considering the trade-off between performance of those models and their interpretability (Baryannis, Dani, et al., 2019). Some of the risks arising in supply chains dealing with perishable products are variations in remaining shelf life. Smart measurement devices, namely a CPS is used to monitor ambient conditions in storages of perishable products. Based on that data, real-time detection of changes in perishability dynamics can be carried out, including a real-time calculation and communication of the remaining shelf life during transportation from one supply chain node to another (Bogataj et al., 2017).

For technologies in the domain of distributed artificial intelligence the supply chain is an interesting application domain. Quite a few approaches exist that leverage multi agent systems for optimisation of processes and ontologies for supporting data-exchange by providing a common semantic layer. In an AgentCities.Net project a multi-agent system for integrated production and logistics planning has been developed. It facilitated the FIPA (Foundation for Intelligent Physical Agent - an IEEE Computer Society standards organization²) contract-net protocol (CNP). The system decomposed the overall planning problem step-wise and used the CNP in a nested fashion to assign sub-problems to different agent types. These agents have then also been responsible to aggregate solutions to sub-problems (Karageorgos et al., 2003).

² <http://fipa.org>

To support a supply chain in the fashion industry, ontological and agent-based systems have been combined (Lo et al., 2008). It solves enterprise interoperability problems by supporting the distributed and decentralized character of supply chains where the ontology on the other hand allows semantic unification and provides a standard vocabulary to query the distributed information system.

Another approach combining distributed computing (again MAS) and semantic web technologies targeted the analysis of big data (Giannakis & Louis, 2016). The system helped to improve flexibility and responsiveness on business level. On a process level it facilitated information integration, and process integration. The approach also helped to improve enterprise interoperability and the ability to handle complex information structures by providing both support for distributed computing, and semantic unification (Giannakis & Louis, 2016).

Inventory and logistics

Inventory control is the process of managing supply, storage, and distribution of stock, with the appropriate quantities to meet customer demand and still maintain minimum stock levels so as to reduce inventory costs and minimize risk of excess items. Internal and external logistics, namely the movement of materials and the support operations that occur within a company are crucial for the effective inventory control. The most of AI applications in this domain are classified into the inventory control function, including stock-taking and tracking, forecasting, back-orders, replenishment rules and ordering policies. Other uses of ML are notable in autonomous robotic operations in internal logistics and transport.

Optimal inventory control can significantly reduce inventory costs related to material, parts and finished goods. ANN have been proven to reduce the total level of inventory by 50% in the organization, while maintaining the same level of probability that a particular customer's

demand will be satisfied (Bansal et al., 1998). ANNs can be used to determine the optimum level of finished goods inventory as a function of product demand, setup, holding, and material costs (Paul & Azaem, 2011). Fuzzy neural network is used to facilitate decision support for managing automobile spares inventory in a central warehouse. It is utilized for forecasting the demand for spare parts (S. Li & Kuo, 2008). Backorder prediction is traditionally based on stochastic approximation, thus overlooking the substantial amount of useful information hidden in historical inventory data (Hajek & Abedin, 2020). Ensemble learning approaches and specific metrics are proposed for identifying parts with the highest chances of shortage prior to its occurrence (de Santis et al., 2017). Machine learning models equipped with an under-sampling procedure are used to maximize the expected profit of backorder decisions (Hajek & Abedin, 2020). Choosing the optimal replenishment rule in the dynamic, fast-changing supply chain environments is a challenge. ML is used for the dynamic classification of replenishment rules (out of 4 alternatives) based on different input features with the accuracy of 88% (Priore et al., 2019).

Inventory is classified based on the different demands, values, revenues they bring in, storage costs, of different product groups. Supervised learning classifiers are used as a superior alternative to simulation, for defining the specific ordering policies for specific inventory classes (Lolli et al., 2019). Perishable products are those whose quality deteriorates through time, for example due to environmental conditions. Reinforcement learning can be used to specify ordering both stock and age-based policies for retailers and thus reduce their costs (Kara & Dogan, 2018).

RFID is today state of the art technology for inventory control of parts, materials, and products. One of the major issues in this area are false positive readings, which refers to tags that are detected accidentally by the reader but not the ones of interest. ML can be used to detect (with 93% accuracy on average) and handle those readings (Ma et al., 2018). Stocktaking workload

is typically very heavy and time consuming. Convolutional Neural Networks (CNN) are used for inventory objects counting and localization by using vision interface (Verma et al., 2016). Machine vision can be used also for acquiring retail shelf inventory data (Kaan & Ying, 2014). It has been found that in some cases (product bulk containers), ML vision methods are more accurate than humans (Kawanaka & Kudo, 2018). Precise tracking of the product flow management in large supply chains is crucial for inventory control. While RFID-tagged products facilitate precise data management, RL can be used to efficiently locate a product deviated from its planned path (J. M. Ko et al., 2011).

Despite the advances in computer vision (Pavlović et al., 2019), RFID assistance is still a dominant approach for positioning of autonomous robots. Some of the major problems of RFID-assisted positioning are often malfunctioning tags and time-consuming creation and maintenance of look-up tables with geo-positions of RFID tags. ML approach, by using SVM algorithm, is proven as a viable alternative to look-up table approach, even with several non-responsive tags for robot self-localization (Yosuke Senta et al., 2007). While autonomous robotic operation in internal logistics (e.g., for stock moves) still involves greater safety risk, reinforcement learning is used to improve human-robot interaction, specifically in terms of imposing robot behaviour change based on observed human-centric information (Oliff et al., 2020). Explainable AI can significantly improve safety and trust in goal-driven robots (Sado et al., 2020).

Internal logistics effectiveness is often disturbed by wrong products' picks in the warehouses' picking stations. Those errors can be significantly reduced by using RFID localization technologies and ML (Geigl et al., 2017).

LSTM models are trained with historical data on sequences of flights for the specific airport and particular aircraft. Then, a transfer learning approach is used to predict flight delays for other companies and other airports (N. McCarthy et al., 2019). There are already existing XAI

approaches that can provide explainability of models based on transfer learning (J. Chen et al., 2018). Detecting anomalous container itineraries are important for implementing anti-fraud measures and ensuring supply chain security. Container Status Messages are used to successfully discover irregular container shipments, by using a simple SVM classifier (Camossi et al., 2012).

With respect to multi agent systems approaches to logistics, some approaches have already been discussed in the supply chain section other approaches - that include logistics aspects are discussed in the advanced planning and scheduling section.

Advanced Planning and Scheduling

At glance, production planning deals with time and resource allocation of production activities at all levels of detail, based on the product bill of material and routings. It considers parts and materials, employees, and production capacities (tools, machines). It takes into account different methods of production. The objective of production planning and scheduling is to maintain accurate estimation of material and resource availability, by considering current production plan and future demand, predicted maintenance and repair, but also different perturbations.

Data mining tasks and methods, and their application in process planning, strategic capacity planning, aggregate planning, master scheduling, material requirements planning, and order scheduling are reviewed by (Ismail et al., 2009).

Production planning is today increasingly dynamic, it steadily abandons static concepts such as dispatching rules and average lead time, by introducing prediction and forecasting methods for experience-based, rather than knowledge-based (rule-based) planning. Dispatching rules prioritise all the jobs waiting for processing on a machine and they are the most commonly used approach for production job scheduling. Q-learning, a widely used RL algorithm is used

for solving a single machine dispatching rule selection problem in agent-based production scheduling systems (Y.-C. Wang & Usher, 2005). Approach to policy selection for order dispatch has been extended in multiple directions. In (Y.-F. Wang, 2020) a multi agent system is used in combination with Q-Learning. Other exemplary approaches increase the adaptivity and increase the speed (Kuhnle et al., 2019; Shiue et al., 2018). Dynamic scheduling implemented by using data-based (Machine Learning) instead of rule-based (dispatching rules) approaches is used to facilitate flexible manufacturing systems. Different methods are used for dynamic scheduling, such as inductive learning, neural networks, and case-based reasoning (Priore et al., 2006). More recently, RL techniques have been used to provide the most effective approach to dynamic scheduling. RL is used to generate a self-optimizing scheduling policy for flexible manufacturing systems (Hu et al., 2020). Reinforcement learning techniques are used to adjust arrivals of parts to a shop floor/work centre and dispatching policies to minimize due date deviations (Hong & Prabhu, 2004). The work of (Waschneck et al., 2018) builds on cooperative Deep Q Network agents (Mnih et al., 2015), utilising deep neural networks. The agents are trained in a Reinforcement Learning environment with flexible user-defined objectives to optimise production scheduling. Traditional systems consider fixed, average lead times for production planning and scheduling. In reality, lead times are variable. Supervised ML approaches can be employed for lead times prediction, relying on historical production data obtained from manufacturing execution systems (Lingitz et al., 2018). Traditional production planning method is hierarchical. Thus, it does not consider the detailed scheduling constraints, leading to inaccurate plans. To address that issue, a method for simultaneous optimization of production plans and schedules is proposed, based on an improved hybrid genetic algorithm (X.-D. Zhang & Yan, 2005). Production and maintenance planning can be considered as integrated, based on the forecasting method that uses energy consumption to identify normal and abnormal machine operations (Morariu et al., 2020).

Maintenance and repair are increasingly important factors for planning, especially in flexible manufacturing systems. Remaining useful life (RUL) of manufacturing systems and components can be predicted, based on historical exploitation data (Carvalho et al., 2019). Random Forest ensemble algorithm is used for predicting machine tool wear with experimental results that outperform more complex methods such as ANN (D. Wu et al., 2017). Tool and machine components wear can also be visually determined; Thus, imaging-based sensors and image classification AI algorithms that can provide local explanations can be used in predictive maintenance (Krishnamurthy et al., 2020). Besides master data, realistic production schedules need to also consider conditions of the machines and tools as they could significantly affect the lead times. Technique for measuring machine conditions appropriate for an integration with production planning and scheduling systems is proposed (Karner et al., 2019). With regard to the deterioration of the machines and tools, the production system is a stochastic system, where uncertain failures are followed by repair and maintenance activities, while both affect product quality. RL can be used to find the optimal trade-off between conflicting performance metrics (Paraschos et al., 2020). Failures can be detected as anomalies, thus addressed with unsupervised ML approaches. Anomaly detection is used to identify the needs for semiconductor equipment maintenance but also to indicate potential line yield problems (C.-Y. Chen et al., 2020). Thus, it is important to have formal definitions of anomalies and faults in machines, controllers, and networks, along with detection mechanisms and associated common framework (Lopez et al., 2017).

Dynamic production planning and scheduling implies that manufacturing costs are not fixed, especially when considering variable capacity load, forecasted maintenance and repair and variable lead times. Explainable AI is used for manufacturing cost prediction for 3D computer-aided design (CAD) models, based on identifying machining features and differentiation of the machining difficulty for the identified features (Yoo & Kang, 2020).

Manufacturing execution introduces uncertainties that are far easier to address in production plans and schedules if the enterprise gains prediction and forecasting capabilities. For example, quality control outcomes and repair of products in repeated or newly introduced operations can be forecasted in some cases. Temperature and vibration data collected during the additive manufacturing process are used to predict surface roughness, by using ensemble learning algorithm (Z. Li et al., 2019). In execution, AI can help to reduce the level of uncertainties also in automated shop-floor logistics. Despite ubiquitous use of autonomous robotic operators, the number of humans in the smart factory is still high, resulting with increased number of human-robot interactions and consequent disturbance and unpredictability. Improving the ability of robotic operators to adapt their behaviour to variations in human task performance is, therefore, a significant challenge, that is being addressed by using RL techniques (Oliff et al., 2020).

A different approach for planning of processes across organisations has been taken in the CrossWork project (Mehandjiev & Grefen, 2010). Here an infrastructure, based on multi agent systems, supports users in a gradual construction of workflows that span multiple organisations. After a model has been established the infrastructure supports the execution of these processes (Mehandjiev & Grefen, 2010).

In the project NgMPPS-DPC (Next-Generation Multi-Purpose Production Systems - Distributed Production Control) an actor-based system (Agha, 1985; Hewitt, 1977) has been created for production and logistics scheduling (Weichhart & Hämmerle, 2017). Actors that represent orders are bidding for time-slots on available machines. A market mechanism where when many order-actors bid for the same time-slot the prices soar orders are scheduled across machines. In addition to this, logistics is considered.

Currently are many sub-symbolic approaches researched with respect to image recognition in industry. A particularly interesting topic for (symbolic AI) planning and scheduling in flexible production systems are approaches that allow to determine humans and robots and work tasks.

Besides being able to determine visual commands for robots in an industrial environment, (Heindl et al., 2019) uses a new approach that allows to get rid of expensive 3D cameras with limited depth detection capabilities. That approach allows to use fish-eye cameras to be mounted on the ceiling of a manufacturing hall, and determine the 3D pose information of human operators and of robotic arms.

Finance and accounting

Accounting information system acquires, stores, and processes financial and accounting data in one enterprise. Accounting activities include different information and/or financial transactions from/to customers, suppliers, tax authorities, investors, and creditors; design and delivery of different types of financial and managerial reports related to the above transactions.

The most significant group of accounting activities which is today assisted by AI is related to risk management and compliance issues. Responsible management implies periodical self-audits of accounting data. Such activities can be automated by engaging semi-supervised ML models to detect anomalies (Bhattacharya & Roos Lindgreen, 2020). Supervised ML classifiers, trained with journal reports data are used to reveal potential anomalies and compliance issues related to VAT regulations (Lahann et al., 2019). ML models are used to predict bankruptcy of the listed companies in China, with test set accuracy of 95.9% (Y. Li & Wang, 2018). Explainable AI, based on deep neural networks and K-nearest neighbour methods is used for predicting corporate financial distress (Chou, 2019). Key reasons and drivers of mortgage defaults can be estimated by using XAI approaches for different groups of loans (Bracke et al., 2019). Knowledge graphs, namely logic-based models can be generated to explain the reasoning of data-driven models, namely ML ones. Such knowledge graphs are proposed for interpreting the actions proposed as a response to company revenue loss (J. Wu et al., 2017).

Some of the risk management activities are directly related to mergers and acquisitions but could be of significant use also in other domains. In acquisition and merger operations, enterprises are keen to verify the accuracy of the financial statements provided. Today, many different ML algorithms can be effectively used for that purpose (Perols, 2011) (Sharma & Panigrahi, 2012). Bulk analysis of a large number of financial documents is often needed in acquisition and merger operations. Explainable AI can be used in their classification, associated with textual-based explanations (Yang et al., 2020). Also, it can detect fake financial news (X. Zhang et al., 2020). For the purposes similar to above, Naïve Bayes ML approach is used to analyse narrative Forward-Looking Statements (e.g., planned revenues or income, future investments, operations, etc) in corporate filings (F. Li, 2010).

In everyday accounting activities, directly matching invoices to the associated purchase orders can be a challenge due to missing order numbers, differences in terms of the invoice amount, quantity and/or quality. ML can be used to build a recommender system for semi-automated matching (Esswein et al., 2020).

AI models are increasingly used in finance for considering credit or loan applications. However, they can be used in preparing one. XAI approaches can provide counterfactual explanations - they expose the minimal changes required on the input data to obtain a different result e.g., approved vs rejected application (Grath et al., 2018). Also, credit risks can be automatically and assessed with provided interpretations (Bussmann et al., 2020).

Product Lifecycle

Product Lifecycle Management (PLM) process coverage includes managing every aspect of a product lifecycle from its design, through manufacturing, to service and disposal. With introduction of cost-efficient IoT technologies, PLM can now also include product exploitation. While the common industrial objective is to extend the PL, in some industries, planned

obsolescence design and manufacturing principle is introduced to ensure that demand for the given product is continuous. Data for PLM can be found everywhere. The various data in the main PLM stages, namely beginning, middle and end of product life are defined by (J. Li et al., 2015).

AI application is found in the earliest phases of PL, namely product design. Explainable AI helps in understanding consumer shopping behaviour and using it to further optimize product design, development, and sourcing (Sajja et al., 2020). ANNs are used for assessing environmental impact of the products in the design and conception phase (Park & Seo, 2003). In fact, reducing production waste is sometimes one of the key requirements, with intelligent manufacturing systems playing the key role in addressing that requirement (Ahmed & Kareem, 2019). One of the main challenges for PLM that is being increasingly addressed by AI is predicting product life cycle cost. Product life cycle cost includes all costs in all stages of product life cycle, including use and disposal. Many different ML models including ANNs are used for predicting the life cycle cost of a new product (H. Liu et al., 2009). Predicting product obsolescence is in direct relation to LC cost. Product obsolescence is a major challenge, driven by frequent technology changes and innovation, especially since it can occur suddenly. ML is used to predict the level of obsolescence risk and the date when part becomes obsolete. RF, ANN and SVM are used to classify parts as active or obsolete with 98% accuracy (Jennings et al., 2016).

Product exploitation and data collected after the product is shipped to customers can help in improving its quality. Lifecycle information, namely after-sales service data is combined with manufacturing process data to build a model which can detect anomalies in the products before they are shipped (T. Ko et al., 2017).

While in exploitation, product support is carried out by customer care. Companies increasingly use conversational software agents or chatbots to provide customer service (Adam et al., 2020).

Expertise and responsiveness are found to be the most important factors for customer trust in customer service chatbots (Nordheim et al., 2019). Besides exploitation, customer care may include maintenance and repair. There are numerous applications of AI in predictive maintenance. ML techniques are continuously used for condition-based monitoring of complex products by using data from some Supervisory Control & Acquisition (SCADA) data. They can also be used to discover temporal and causal relationships in that data and thus, explain the anticipated fault risks (Chatterjee & Dethlefs, 2020). Interpretability of predictive maintenance models is critical for industrial domains where compliance, transparency and trust are especially important, such as aerospace engineering (Shukla et al., 2020). For example, explainability can contribute to improved human assistance in fault recovery (Das et al., 2020).

In the end-of-life PL stage, products are often returned to a manufacturer for scrapping or remanufacturing. Recycling and remanufacturing companies use scrapped products to recycle or remanufacture with uncertain timing and quantities of the returns. Due to those uncertainties, stochastic models are more often used for forecasting returns (Zhou et al., 2016) than ML (Taghipour, 2021). Industries are increasingly pressured by environmental legislation to consider end-of-life treatment of their products. One option is to use used parts to manufacture new products. ANN are used to analyse degradation of the component, in combination with traditional methods for time-to-failure prediction (Mazhar et al., 2007). For the illegally scrapped products with significant environmental impact, traceability to the manufacturer is important. Tracking and attribution of the material or product in exploitation can be done even without the RFID-based methods. For the specific products, ML method is used to suggest the attribution of the material to the particular manufacturer, with the accuracy of 89% on the test dataset. This is often needed in forensics (Casale & Dettman, 2020).

For the integration of multiple systems during the product life-cycle (and across multiple enterprises) multi agent systems have been researched (Karasev & Sukhanov, 2017; Yadgarova

et al., 2015). The systems support integration of distributed systems that are needed during the lifecycle of a product - ranging from the design and engineering over manufacturing to recycling. This way the MAS communication layer provides semantic unification.

Human Resources

Human Resource Management aims at gaining and retaining talent and maximizing the performance of employees. It includes activities such as recruitment, training and development, human resource allocation, performance assessment and reward, managing payroll and others. AI facilitates existing activities by making them more cost efficient, thereby making possible even to implement tasks which were not considered viable without access to relevant big data and their processing capabilities.

The most significant application of AI methods and approaches is clearly visible in recruitment. ML models make it possible to predict the successful placement of a candidate in a specific position at a pre-hire stage. They can be also used to provide a balanced recruitment plan while improving both diversity and recruitment success rates (Pessach et al., 2020). ML are used for semantic matching (job description vs resume) and candidate ranking, while personality characteristics can be inferred from the candidates' social network posts (Faliagka et al., 2014). Big data accessible on social networks is now an important resource in recruitment. Content-based recommender systems (based on the trained SVM models) are used to propose jobs for Facebook and LinkedIn users, based on their interaction and social connection data (Diaby et al., 2013). As the number of applications per advertised job position can grow very high, employers are challenged to find suitable candidates manually. Attention-based BERT model is used to automatically parse resumes and rank candidate resumes based on the suitability to a job description (Bhatia et al., 2019). Modern text classification approaches are now used for better matching of resumes to taxonomies of job categories. Automatic text document

classification system that utilizes ML makes it possible to implement a scalable classification system for a large taxonomy of job categories (Javed et al., 2015). However, there is a growing concern of ethical issues in making automated decisions in recruitment. There are studies that have shown biases in ML models in recruitment, even a correlation between the facial features and candidate ranking. The training data must comply with the very specific ethical guidelines, based on fairness definition, methods, and tools (Mujtaba & Mahapatra, 2019).

Another HRM task that can be assisted or even automated by using AI is resource allocation. ML algorithm is used for human resource allocation in projects, based on desired cost, time and/or quality criteria. The model is trained with allocation strategies used by the organization over time (Kieling et al., 2019). Resource allocation activities may be even used to protect companies from inappropriate allocations. Namely, some ML classifiers can be effectively used to estimate specific human based information security risks within acceptable error rates (Eminagaoglu & Eren, 2010).

Very important context of AI use in HRM is defined in the domains of corporate training and knowledge management. While digitalization introduced effective online education methods in corporate training, AI is found to facilitate improvements in the areas of customized educational content, innovative teaching methods, technology enhanced assessment and communication between student and lecturer (Chassignol et al., 2018). Other AI-assisted innovations in education are: adaptive learning, personalization and learning styles, expert systems and intelligent tutoring systems (Sisman-Ugur & Kurubacak, 2019). There are specific opportunities for using AI in corporate training and HR development, addressing more personalized training needs, micro-learning, accessibility, employee engagement and extent of training transfer (Maity Souvik, 2019). There are many areas of knowledge management (KM) in which AI can contribute to significant improvements, such as knowledge discovery and acquisition, search and retrieval, natural language and speech interfaces to KM systems,

summarization, distribution/push, and analysis (Liebowitz, 2001). Predictive and explanatory models based on ANN, SVM, decision trees and logistic regression are used to demonstrate the strong and positive correlation between the implementation rate of Knowledge Management practices and organizational performance (Delen et al., 2013).

Corporate culture has a profound impact on employee performance and indirectly, on important business outcomes. ML and NLP are used to analyse different corporate documents to assess correlation of the corporate cultural values of innovation with operational efficiency, risk-taking, earnings management, executive compensation design, firm value, and deal making (K. Li et al., 2018). Employee satisfaction is directly correlated with productivity and thus overall business performance. Sentiment analysis, namely the Linear Discriminant Analysis method was used to prove that firm earnings are dependent on employee satisfaction (Moniz & de Jong, 2014). Employees' engagement, retention and satisfaction can be assessed by using their communications on social media platforms (Costa & Veloso, 2015). Those assessments are very important as they can help organizations to retain talents. HR policies can be significantly improved by considering the insight into the XAI-facilitated interpretations of models for predicting employee attrition (Sabbineni, 2020).

Services for AI-enabled EIS

With implementation of AI services, enterprise becomes more observative/aware, because CPS and AI improve or facilitate access to huge amounts of data in its business environment; it becomes more autonomous, by automating decision making with agent-based and mature RL methods or by significantly improving awareness of existing automation and robotic systems. Finally, enterprise becomes smarter, since sub-symbolic AI makes it possible to learn obvious or hidden patterns and correlations in data, which then can be used for more accurate

predictions and forecasts. Such learning capabilities allow a system to automatically adapt to changing situations.

AI helps to dramatically improve the accuracy of analytical functions that have been implemented with considering significant approximations and simplifications, such as average lead time, average or naïve forecasting, static dispatching rules, etc. AI helps enterprises to transform the perception of perturbation and stochastics in the operations to deterministic considerations. It helps understanding and explaining the occurrences that were not considered in traditional planning and control. For example, supply chain risks (e.g., delivery delays) can be predicted, and observed events are translated into semantic models. Having understood a phenomenon, AI algorithms can in turn then be used to plan mitigation activities (e.g. re-scheduling takes place to optimize the production according to the new situation; tool-usage times are updated). Finally, AI facilitates the introduction of completely new functions that have not been possible earlier due to inability to access the needed data, or to process them fast enough. The examples of such functions are computing dynamic prices in real time, forecasting demand for spare parts, lead-time prediction and real-time inventory monitoring.

In order to make all this possible, three critical elements for the high-level architecture of AI-enabled EIS need to be met. First, EIS must ensure that infrastructures for storing both unstructured and structured data (including storage of non-trivially structured data like graphs), including maintaining updated dictionaries, taxonomies and ontologies for describing that data (i.e., meta-data) exists. Second, EIS must ensure implementation of services, including data acquisition services, data mapping and translation, and data-driven and logic-driven AI services. Technical details of services implementation are dependent on the concrete enterprise architecture (e.g., multi-agent-systems based message-oriented middleware). Third, an AI enablement hub provides continuous, managed, and secure access of AI services to data storage infrastructure components. Besides technical interfaces, AI enablement hubs need to

implement maintenance of dependencies (mapping and alignment of data with meta-data, ontologies) and process logic. Such a hub needs to support the implementation of processes and work-flows, which e.g., combine data mining services with a service to extract meta-data from the repository of external APIs and a service to acquire data and a service to store it in a data-lake). AI enablement hubs will facilitate the implementation of so-called Intelligent Digital Mesh, the interplay of people, devices, content and services for the smarter manufacturing (Uysal and Mergen, 2021). The hubs provide the blueprint for Smart Manufacturing Collaborative System (Zhang & Ming, 2019).

Elements of the high-level architecture of AI-enabled EIS are illustrated in Figure 2.

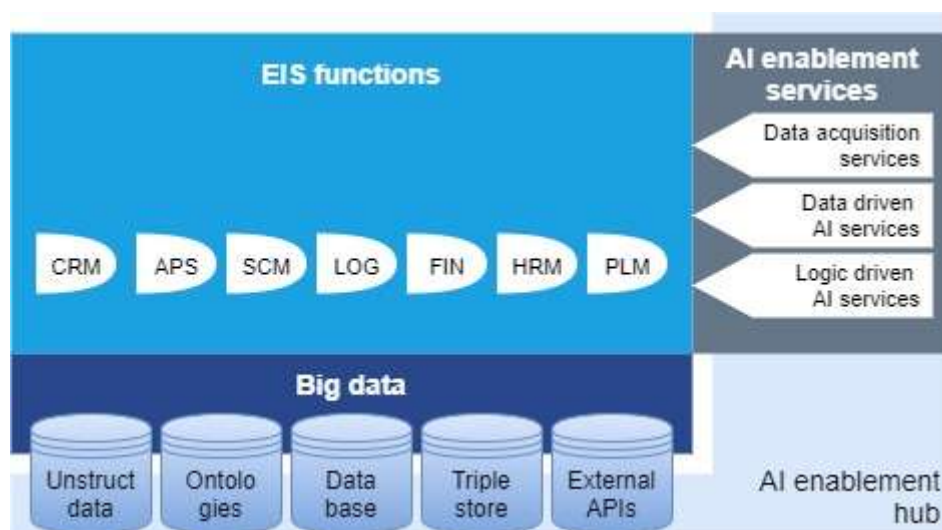


Fig. 2 Elements of high-level architecture of AI-enabled EIS

In the remainder of this section, the initial list of AI-enablement services is synthesised, based on the literature review presented in Section 3. For each of the EIS functions, a list of services is identified with initial evaluation in terms of their individual impacts on the enterprise.

We have selected four indicators to show the main impact of a particular service. The time/cost indicator addresses savings in time and/or money associated with service implementation and use. Flexibility indicator relates to improved enterprise capability to change plans and adapt to the changing environment, customer behaviour, etc. Quality is related to the increase of the

quality of a product, activity, or a process. Income indicator is almost exclusively associated with customer relations and sales function. While each of the services may be associated with multiple impacts, we have chosen only one for each of them, the one with assumed most direct relevance. For example, direct sale chatbot service introduces savings in time and cost by implementing targeted sales strategy, adapted to particular customers. However, the bottom line is that it increases enterprise income as it helps to close the sales which may not be that easy to close by using only human power.

The first EIS function addressed is Customer Relationship Management and Sales. A list of customer relationship management and sales AI services is displayed in Figure 3. The majority of AI services in this domain could have a significant impact regarding increased enterprise income. AI can help to acquire otherwise invisible leads and opportunities from different sources. Customer profitability assessment and predicting customer behaviour are novel approaches to increasing sales by focusing sales contacts on the clients of the highest values or those likely to move away. Direct sales now facilitated by the chatbots fully aware of each of the customer preferences could have a significant impact on the sales income. Customer behaviour prediction, cross-sale and up-sale product recommenders and dynamic pricing build up on the variety of sales tools, now easily accessible to the sales agent or a bot, to extend or to increase its sales. Significant time/cost savings can be made through automation of typically human effort-consuming such as social media marketing, but also by implementing cost-effective approach to sales pipeline maturation. Having the accurate image of the future often means that you can control it. Thus, ability to forecast sales, at the level of supply chain or in retail, results with increased level of flexibility for enterprises to fit new orders or ventures in the known future.

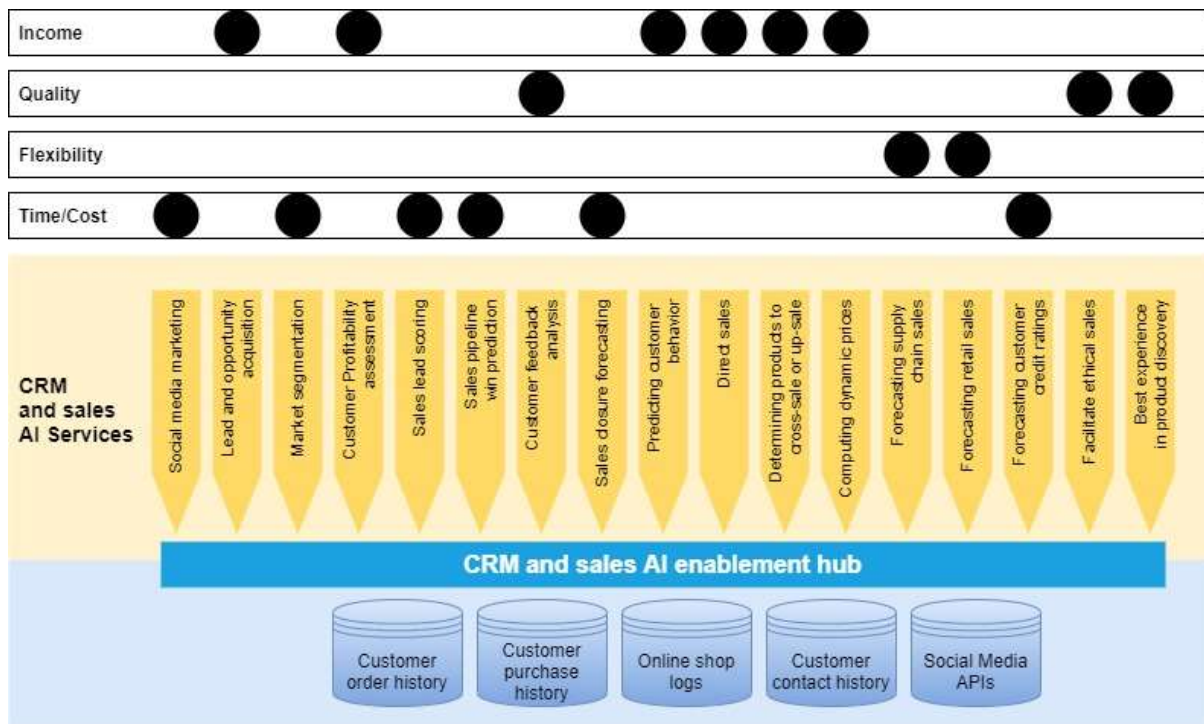


Fig. 3 Customer relationship management (CRM) and sales AI services

Unprecedented levels of disruption introduced by new AI services impose strict commitment to achieving or improving to the highest level of product and process qualities. Dealing with so much customer data is not possible without the strict compliance to the ethical standards in sales. Some of those new services can directly improve the quality of the product or the customer experience.

Despite quite a long list of AI functions, their dependency on data is rather straightforward and exclusively related to the data concept of the customer. AI functions in customer relations and sales require data about overall customer behaviour, including his/her orders, purchases, contacts, and online shop behaviour.

Supply chain formation is a time-consuming activity which includes matching the requirements, assessment of capabilities and capacities, negotiating complex agreements and other tasks. Collaborative Networked Organizations have introduced a paradigm shift by laying out the framework for swift creation of so-called Virtual Enterprise, on the occurrence of the

as big data mapping and transformation requirements makes a supply chain context a perfect candidate for using ontologies and other formal-logic paradigms. Data requirements include capacity, availability and constraints data about SC partners, demand history, price and cost history and product manipulation requirements. However, what is the most challenging is the need to facilitate a central view and alignment of data on individual partners' production and delivery plans and schedules, as well as actual timings in the past.

Inventory and logistics AI functions are displayed in Figure 5. Aiming at maintaining optimum inventory levels, inventory control is one of the most important drivers for cost reduction. Costs related to the time spent in counting products in stock are significant and can be reduced by using machine vision to monitor inventory in a real-time. Flexibility of the AI-enabled enterprise can be improved by introducing prediction and forecasting capabilities, in the Maintenance, Repair and Operations (MRO), back-orders and by introducing different error handling/risk management activities in the process. AI services can also bring qualitative improvements to the inventory and logistics processes, in specific transport and internal logistics processes.

Inventory and logistics AI services and corresponding models depend on historical demand data, which are critical for maintaining optimal inventory levels. Paired with historical inventory levels and location moves, they provide strong empirical basis for supervised learning models. Historical MRO data is used in forecasting the demand for spare parts. Other data requirements include product-focused data, namely warehouse camera feeds, RFID tracking data and product transport location data. Finally, access to transport companies' itineraries and actual timetables is a valuable resource for prediction problems related to external logistics.

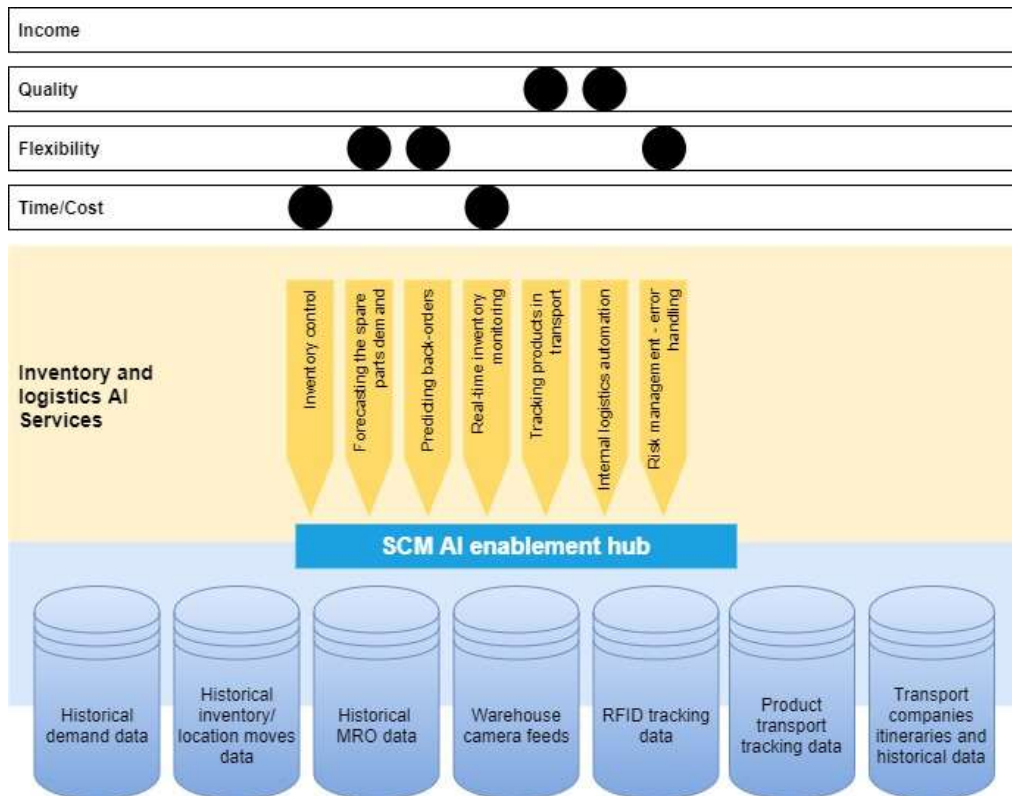


Fig. 5 Inventory and logistics AI services

Production planning and scheduling can significantly benefit from innovative or supporting AI services especially in context of time/cost reduction and improvement of flexibility. Data mining approaches to vast and diverse data, improved production scheduling and especially now fulfilled promise of dynamic scheduling will shorten the production job cycles and thus introduce significant savings. Improvements related to flexibility gains are even more notable. Integrated planning and scheduling, even in collaborative context makes it possible to carry out the simultaneous optimization of plans at different levels of detail. Lead times prediction is one of the key enablers for dynamic scheduling facilitating more accurate planning. Innovative functions that were made possible by AI are prediction of manufacturing costs and even quality of products. Finally, production flexibility is improved by advanced capabilities to deal with uncertainties, such as faults, failures, tool wears, etc. Quality of products and processes can be improved significantly in the execution phase. AI can help to adjust schedules in the real-time

and certainly improve the production safety by facilitating better human-robot interaction.

Production planning and scheduling AI functions are displayed in Figure 6.

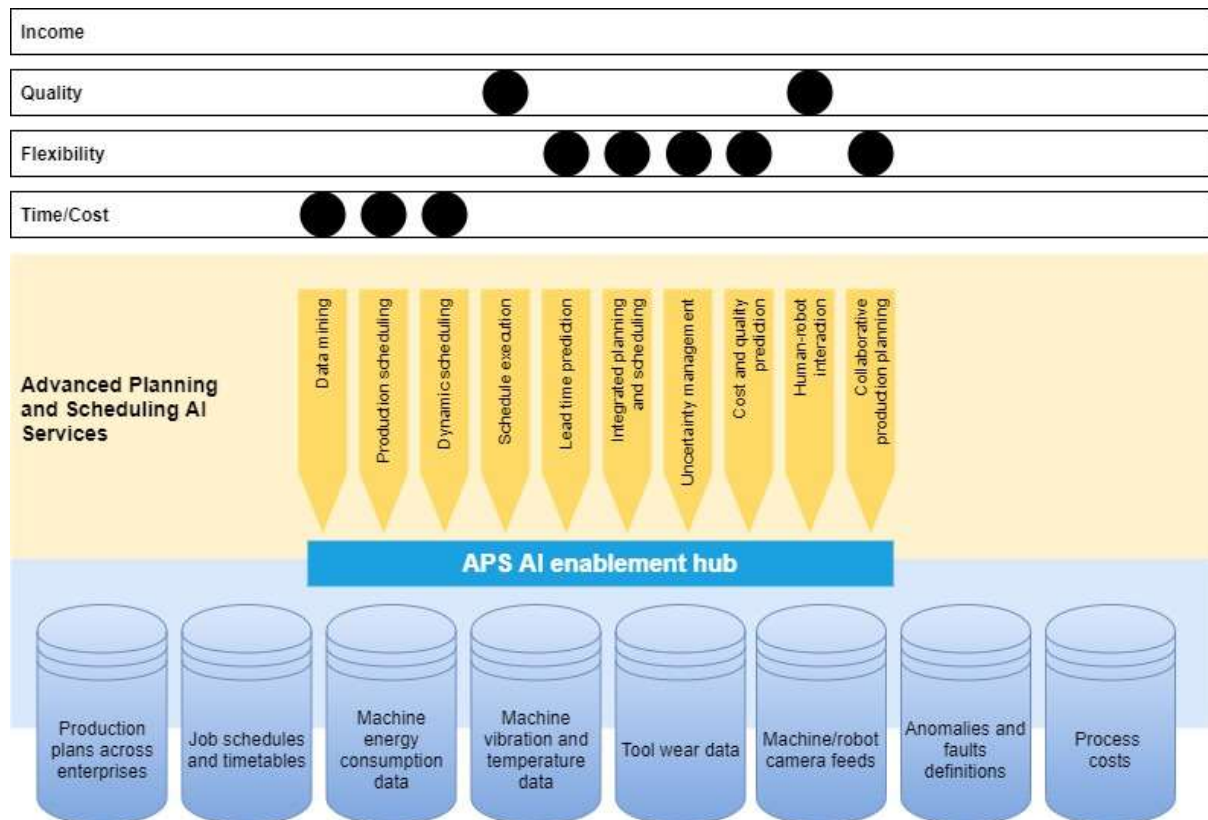


Fig. 6 Advanced Planning and Scheduling AI services

Data required to train the models for the above sub-symbolic AI functions, and the data required for optimisation systems do not stretch beyond the production planning and execution stages.

It includes production plans (across collaborating manufacturing enterprises), job schedules and actual timetables and process costs. Mostly for uncertainty management, required data feeds from the job shop are machine energy consumption, vibration, tool wear and temperature data, camera feeds (robot and with machine/tool coverage). In order to develop the specific strategies for uncertainty management, having anomalies and fault formal definitions is crucial.

Finance and accounting AI functions are displayed in Figure 7. In general, competitive advantage in finance and accounting is achieved by the capability to process vast data fast (which would otherwise require significant human effort) and act accordingly. This capability

implies potentially huge time and cost savings. On-time detection of anomalies in accounting data mitigates the risks of significant damage made to the enterprise by fines and penalties. Even automated corrective tasks recommendations to anomalies, for example by fixing missing references between documents are now realistic functions of accounting systems. AI-enabled detection of anomalies and corrective tasks recommendation saves notable human effort typically invested in self-auditing activities. Financial text analysis can now be performed in real-time by the agents and driven by explainable NLP models. Financial distress prediction is a completely new capability of enterprise, made possible by the AI services. Such prediction function includes explanations and interpretations that could help mitigating the risk of distress by revealing the appropriate action to address that risk. Obviously, this capability introduces a significant increase in enterprise flexibility. Misrepresentation of income by financial fraud can be much easily detected today, in self-auditing or acquisition and merger operations. Also, income in some generic sense may be improved notably by using AI in support of credit application.

Data requirements for the models needed to implement above AI services are straightforward and they include accounting journals (namely, a datasets of all transactions), financial statements, orders and invoices, credit/loan documentation and access to financial news APIs.

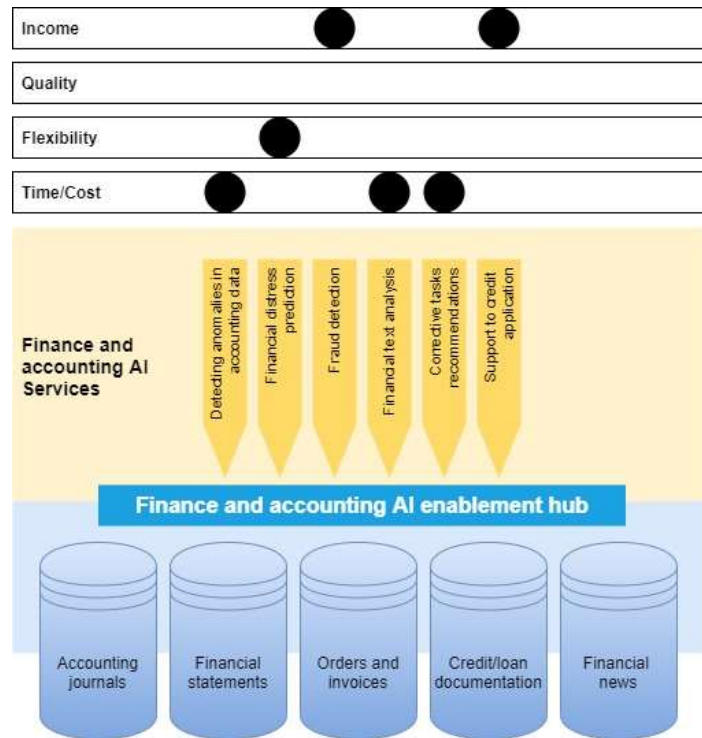


Fig. 7 Finance and accounting AI services

Product Lifecycle Management is an infrastructure function of EIS which spans the full range of other functions, from product design and engineering to dealing with obsolescence and scrapping. Insight into the product situation across all those functions, combined with analytical power to process that insight (both enabled by AI services) provides an enterprise the capability to make earlier and more optimal decisions and thus, reduce costs, improve quality, and facilitate flexibility. Automated customer care in which manpower is replaced with chatbots could have a significant impact on the costs. Product design and engineering now empowered with the recommendations driven by a full product lifecycle data will notably improve the quality of the product. Number of new capabilities related to prediction and forecasting, such as predicting product lifecycle cost, product obsolescence and scrapped products' returns makes it possible to gain flexibility by early treatment of important indicators still to be acquired in the future.

In order to implement the AI services above, vast, and diverse data from the full span of the product life-cycle is required. This data includes but is not restricted to product Bill of Materials, product environmental impact data, product customers' online shopping behaviour, maintenance history, after-sales service and product customer care data, product use and service manuals, product faults, degradations and malfunctions data and returns history.

Product Lifecycle Management AI functions are displayed in Figure 8.

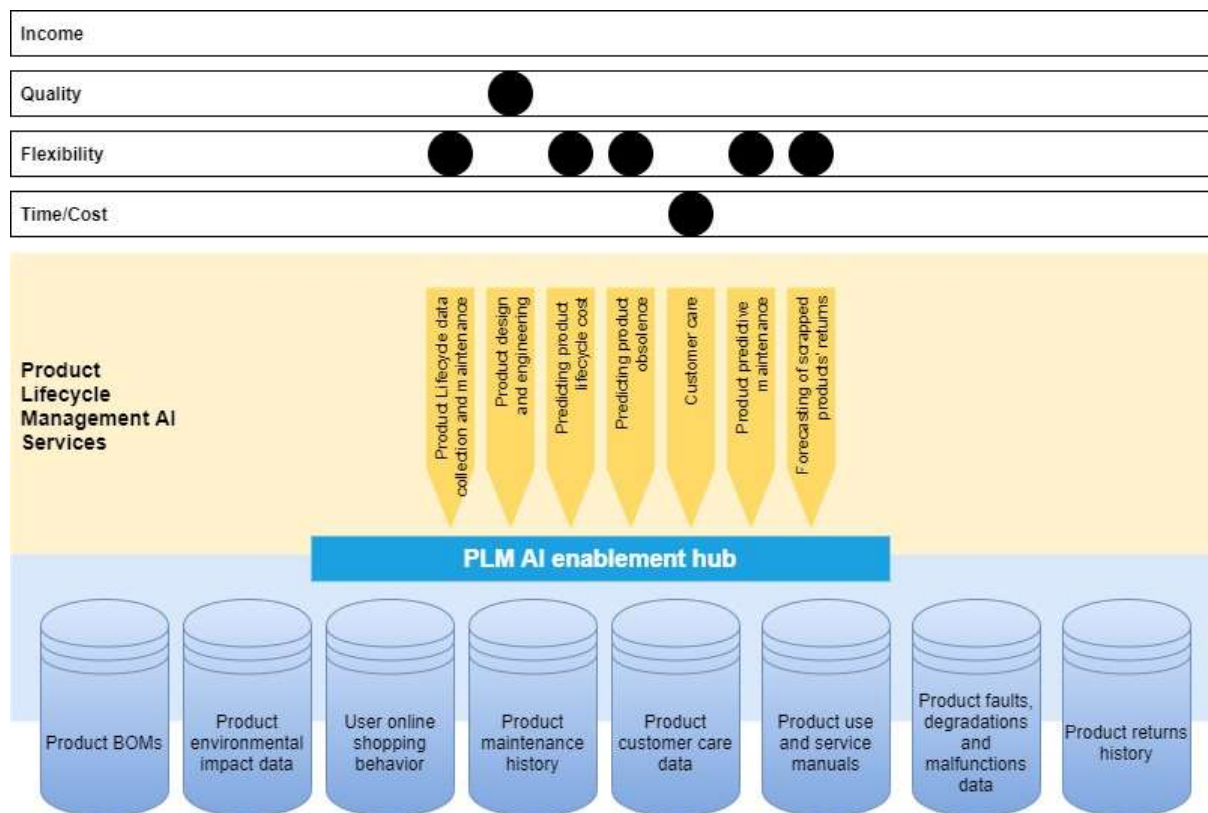


Fig. 8 Product Lifecycle Management AI services

The most notable impact AI enablement can bring in this domain is related to improving the quality of the different processes, in terms of decisions related to recruitment, allocation of the most suitable employees for the appropriate tasks, education and training and corporate culture assessment. Flexibility of HR practices can be significantly improved by timely consideration of the factors specific to employee attrition, by facilitating effective employee satisfaction assessment and by forecasting the actual attrition. In addition, effective knowledge

management practices, now improved in terms of AI-assisted knowledge discovery and acquisition, search, and retrieval, can reduce the negative impact of staff turnover. Last but not the least, the potential of AI approaches to mine structured data from unstructured sources (such as resumes or social media profiles) will diminish the costs of up to now manual work such as parsing and ranking candidate resumes and recruitment by using social media.

Human Resources Management AI functions and data requirements are displayed in Figure 9.

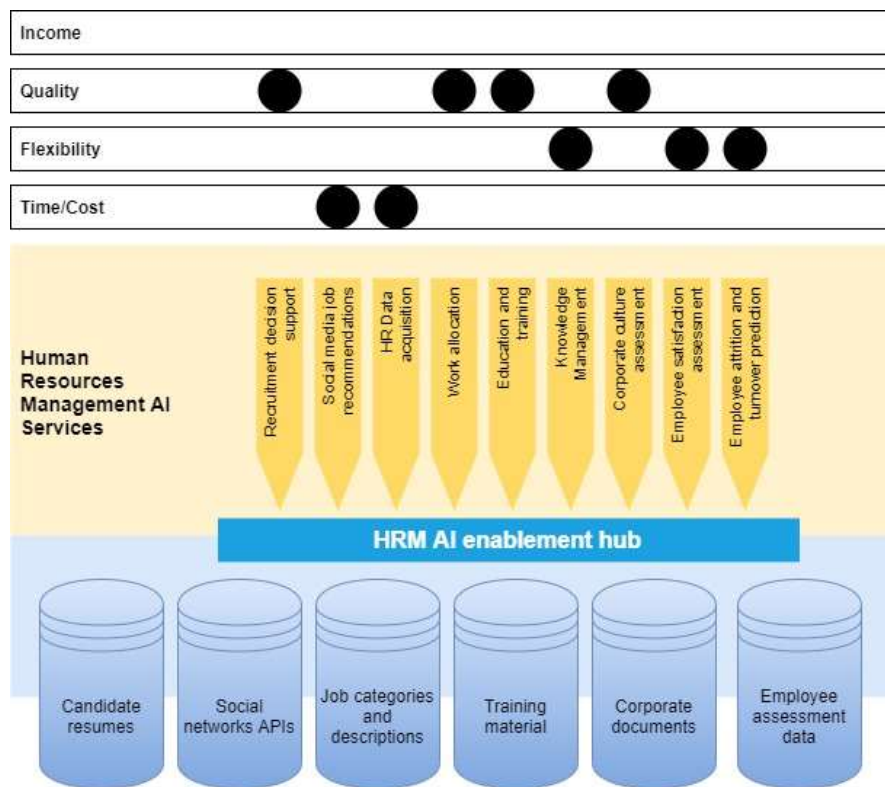


Fig. 9 Human Resources Management AI services

Conclusions

We have analysed the contributions of symbolic and sub-symbolic AI to different functions of Enterprise Information Systems (EIS), namely: Customer Relationship Management and sales, Supply Chain Management, Inventory and logistics, Production planning and scheduling, Finance and accounting, Product Lifecycle Management and Human Resources. The choice of functions is based on the experience of the authors, according to the relevance to the

manufacturing systems; we are all aware that more systems could have been added and that the borders between those functions are sometimes quite blurry (in practical implementations). For every function, we have conducted a literature review with respect to improving the effectiveness or efficiency of the existing tasks or creating completely new tasks, where this improvement is brought by the AI technologies. Every contribution is discussed from the functional point of view; quality of the cited approaches was not therefore assessed. In the last but one section we have reflected on the requirements of a platform that aims at bringing together different AI-enabled services. Those requirements are not the result of some systematic design process and they not involve the discussion with the key stakeholders in EIS landscape. Instead, they are only the interpretation of identified capabilities of EIS, made possible by AI. That section aims at informing the readers from innovative manufacturing enterprises about vast and diverse possibilities of AI-based services and the basic infrastructure required to integrate those (on a high level of abstraction). Until now, we have observed AI in only very narrow implementations in industry. Having 360 degrees view of AI applications in end-to-end processes of manufacturing industries provides the context of the future design and development activities. The context, on a very high-level is given by the concepts of big data storage and definition infrastructures, AI services and AI-enablement hub.

Big data infrastructure provides critical functions such as storage of large amounts of structured (tables, SQL), semi-structured (xml/json messages) and unstructured (video streams) data, definition of their semantics (through meta-data, taxonomies, ontologies, etc.) and provides controlled access to that data. This infrastructure includes also maintaining information about external data sources through agents, bots, and APIs. It implements the tools for creating and maintaining flexible backup strategies. In big data world, costs are important. Typically, they are managed by considering and combining cloud vs. local storage options. Data-lake storage architectures, by definition, provide a central place that holds all these different kinds of data

and also provides access to it. In more distributed settings different servers and services store different data-types. AI-enablement of EIS will lead to new and changed data-types. For example, the information objects (on semantic level) will get additional data-fields that describe some properties of these objects. Enriched information objects need to be accessed by services that are built on the old structure of the objects.

AI services are envisaged as local or third-party services, accessible in the context of individual access or orchestrations in which several services are combined to add value to the specific enterprise function. They are implemented within the limits of EIS or outside of it, within the enterprise or beyond. The above decisions are, similar to data storage, the outcome of the cost optimisation process.

The third component is the AI enablement hub. It provides access to multiple of these AI and data infrastructure services. It also must also enable users to build a workflow that allows them to integrate multiple services. AI enablement hub must support data acquisition, transfer (eventually across company boundaries), and translation to match different ontologies used by consumers of that data. A challenge here is to maintain interoperability despite the dynamics of the connected systems. By using the ontologies hub will allow reasoning over different data structures within or outside enterprise limits and support translating data between data structures that follow different ontologies.

The expected impact of the research behind this paper, expressed in the guidelines for the follow-up activities is multi-fold. The elements of the high-level architecture are the placeholders for the future research in the development of individual AI services and potentially valuable guidelines for refactoring of the industrial architectures. Future work may be related to addressing multiple challenges related to integration/interoperability through the AI enablement hub, including orchestration and choreography of services and AI-enabled custom business processes. Relevant follow-up is the design and implementation of the CPS

and agent-based infrastructures for data acquisition. The complementary research may include review and evaluation of reference datasets for training the models for AI-enablement. Finally, a survey research to estimate the rate of improvement in each of the indicators and thus confirm or deny the assumed impact in this paper would be highly beneficial.

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