The Role of AI Platforms for the Servitization of Manufacturing Companies

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Abstract The paper sheds light on the interplay between the adoption of digital platforms for Artificial Intelligence (AI) and the servitization of manufacturing companies. Through the analysis of three cases that have been deployed with a commercial AI platform to provide advanced services such as health monitoring and predictive maintenance to industrial equipment and infrastructures, we conjecture about how manufacturing companies could benefit from the adoption of this kind of platform in their servitization journey.

Keywords Servitization · AI · Digital platform

1 Introduction

The success stories of companies such as Uber or Airbnb are notable examples of the large diffusion of platform-based businesses, in which the value is created and captured by first enabling demand matching, and then facilitating transactions between customers and suppliers. These businesses are always characterized by the

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S. West et al. (eds.), *Smart Services Summit*, Progress in IS,
https://doi.org/10.1007/978-3-030-72090-2_9

presence of an internet-based infrastructure (i.e. the digital multi-sided platform) that, as defined by the literature (Ardolino et al. 2020), enables the interactions among two or more different groups of users (i.e. the different sides of the platform,) through a virtual environment (i.e. an app, a website, etc.). Platform-enabled business does not only concern consumer sectors, where marketplace like Amazon and Alibaba have taken the lead over "brick and mortar" competitors, but also B2B settings in which other categories of industrial platforms are emerging. For instance, Internet-of-Things (IoT) technologies and their applications are experiencing great diffusion thanks to solutions such as Thingworx by PTC or Mindsphere by Siemens. These platforms are used to connect equipment, collect, store, organize and analyze field data (on the Cloud), generate insights, and enable the provision of data-driven, proactive services. The spreading of the mentioned platforms in the form of Platform as a Service (PaaS) can facilitate to a large extent the servitization of manufacturing firms: using an industrial internet platform, the equipment manufacturer can focus on the provision of intermediate and advanced services such as condition monitoring, remote control, preventive maintenance, and customer support, rather than just selling their products and forgetting the needs of professional customers along the product lifecycle. The trend to develop advanced services through the use of digital technologies has been named "digital servitization"(Paschou et al. 2020). Despite its growing relevance, how digital servitization can be implemented in practice remains rather unexplored. In particular, little work has specifically focused on how companies can manage data and information gathered from the field, to develop advanced services. In addition to IoT and industrial internet platform, also Artificial Intelligence (AI) seems to fit naturally with the servitization strategy (Iansiti and Lakhani 2020) and have proven to be useful in this business setting (Paschou et al. 2018). Despite this popularity, it is claimed that most initiatives developing AI do either completely fail or not reach the expected goals: companies find hard "augmenting" the human skills with AI models since there is a paucity of professional competencies such as business analysts and data scientists (Xing et al. 2015). A great help could come from the advent of a new category of digital platforms, namely AI platforms, that are specifically designed to facilitate the development of AI applications (Porter and Heppelmann 2015). Big vendors such as SAS, IBM (Watson), and Microsoft (Azure) are claiming that their solutions can speed up to a great extent the servitization journey of a manufacturing company since it can use AI platforms to develop and deploy diagnostic models that can be trained (and retrained) on the huge amount of data that are so far collected by its installed base. AI platforms include also features that automate—to a large extent—the typical tasks requested in digital servitization, such as data collection, cleansing, normalization, ingestion, selection of the most appropriate algorithms, verification, training, validation, etc. These platforms are usually conceived to support the deployment of the AI models along their lifecycle and with features that help the construction and distribution to the equipment users (i.e. operators and maintenance crew) of dashboards. In this sense, these platforms can be of great help in increasing the diffusion of AI applications and the development of data-driven models and advanced services, in the servitization domain.

Based on the above considerations and since academic research on the role of the AI for servitization is in its infancy, it is of great interest to answer the following research question (RQ): how these platforms could support the servitization of manufacturing companies?

Starting from these gaps, through the investigation of AI applications that have been developed with AI platforms, this paper aims at shedding light on the potential contribution of these platforms to the servitization of manufacturing companies. In line with these premises, the rest of the paper is organized as follows: Sect. 2 presents a short background on AI platforms and servitization concepts, Sect. 3 illustrates the research strategy, Sect. 4 presents the selected cases, and Sect. 5 draws some considerations from the cross-case analysis. The paper ends with some concluding remarks in Sect. 5.

2 Background

2.1 AI Platforms

According to the well-known Magic Quadrant of Gartner corporation Den Hamer et al. 2020), an AI platform needs features supporting at least the following processes: a) collecting and preparing data; b) building models; c) deploying those models along the lifecycle (through dashboards). These features, according to the CRISP-DM method (Wirth and Hipp 2000), are characteristic of a data mining project, since they are means for the data understanding and preparation, modeling, evaluation, and deployment phases. Other premium features relate to the level of automation of the different coding tasks (e.g. simple/low efforts/one-click features, etc.), and the ease-of-use. The market leaders in this domain (e.g. SAS, RapidMiner, KNIME, etc.) have different AI algorithms for classification, regression, prediction, clustering, as well as functionalities for automating building and testing models.

2.2 Servitization

The term servitization refers to the shift of manufacturers from selling products to offering product-service solutions, where more and more services are tightly coupled to the product to increase the value potential of this new offering (Baines et al. 2007). The interest in this topic is growing among academia, business, and government because it is thought that a move towards servitization is a mean to create additional value-adding capabilities for traditional manufacturers(Baines et al. 2009). It is considered a strategic alternative to product innovation (Carlborg et al. 2013) and standardization (Baines al. 2009), a way to meet increasingly more heterogeneous needs while exploiting scale economies from high-volume production (Hart 1995;

Baines and Lightfoot 2014). This transformation is having a deep impact on the business of the manufacturing sector. Nowadays, the application of digital technologies can further advance servitization, by enabling more and more sophistication of the service offerings (Carlborg et al. 2013) and the development of new service-oriented business models (Brax 2005). Notable cases have already shown this potential and the rationale for such a shift, and also smaller companies are increasingly interested in the adoption of digital platforms to collect and elaborate field data from their installed base, to include advanced services like predictive maintenance or pay-per-use models (Ardolino et al. 2018; Fu et al. 2018). This trend has been named "digital servitization", that is "the development of advanced services and/or the improvement of existing ones through the use of digital technologies by enabling new digital business models, finding ways of co-creating value, generating knowledge from data, and improving a firm's operational performance" (Paschou et al. 2020).

3 Research Strategy

We use case-based research (Yin 2015) since there is little knowledge on this topic, and this research is explorative and early-stage. In particular, we evaluate the impact of AI platforms application in the development of advanced services in different cases, manufacturing companies belonging to different sectors.

First, the selection of the AI platform based on the requirements previously explained, in relation to the -known Magic Quadrant of Gartner corporation (Den Hamer et al. 2020). We selected an AI platform that has been developed by a niche software company and that is currently used by a network of professionals, consultants, and data scientists. We had the opportunity to receive a demo of one AI/ML platform and to enter in touch with the platform provider that also showed a clear interest to be involved in this research.

Then, for the selection of the use cases, with a retrospective approach, semi-structured interviews have been conducted—to provide deeper insights (Barriball and While 1994)—with the platform provider to investigate representative use-case, that have been selected based on the following criteria: (a) the application should have been developed with a clear business purpose (e.g. reducing costs of maintenance, predict performance/ degradation, reduce downtime, etc.); (b) its triggers should have been clearly identified (for instance, partly funded by public R&D frameworks, a change in regulations, a requirement of the customer's customer, etc.); (c) the process from its beginning to the deployment of (even preliminary) results (e.g. a dashboard to the end user) should have been completed; (d) the contexts should have been mostly related to industrial equipment and productive plants (B2B settings) to be maintained and supported along their life cycle; the OEM as well as the owner/operator of the equipment should have either been involved in, or have triggered or commissioned the project; (e) any cultural, organisational and technical challenges faced during the project should have been reported, in order to shed lights on how the corresponding obstacles had been overcome, being these obstacles related to the different stages (data preparation, model building, etc.).

In the end, the results of the findings have been shared and discussed between the authors to highlights the most relevant patterns and draw conclusions.

4 Cases Description

The cases have been selected based on the criteria stated in the previous section, among the customers that have developed advanced services thanks to the AI platform (i.e. Rebecca AI) of the platform provider. This platform has been designed to enable end-to-end management of AI solutions, from data collection (through databases or IoT) to machine learning model development, implementation, validation, and deployment in the production environment (see Table 1). It consists of three main modules ("apps"), namely (a) Builder, (b) Innest, and (c) Frame. (a) Rebecca Builder allows the user to build and train intelligence efficiently and seamlessly, without the need to code. This is composed of three further submodules, respectively "Dataset", "Flows" and "Model". In the "Dataset" workspace, data can be visualized and compared in predefined visualization tools that enable interactive data cleaning operations. Filters can be applied to the raw data to obtain the most suited dataset for model training and evaluation. In the "Flows" workspace, several machine learning algorithms can be implemented to solve supervised (regression and classification) and unsupervised (dimensionality reduction and clustering) tasks, by explicitly selecting their hyperparameters or by adopting a grid-search approach. In the "Model" workspace, the model performance can be evaluated on a test dataset through dedicated visualization tools and performance metrics such as the mean absolute squared error (MAPE) and the mean squared error (MSE) for regression, or precision and recall for classification. The best performing model can be published in the (b) Rebecca Innest module where it becomes available to be deployed in the production environment. Models published in Innest can be connected to the data streaming in real-time through Rebecca IoT, and the model prediction visualized in (c) Rebecca Frame module. Standard visualization can be enriched with tailored dashboards and data experience functionalities, and it is possible to set customized alerts based on the model output.

Table 1 Rebecca modules and sub-modules in relation to CRISP-DM method phases

Rebecca modules	Rebecca sumodules	Corresponding phases of CRISP-DM method
Builder	Dataset	Data preparation
	Flows	Modeling
	Model	Evaluation
Innest	–	Deployment
Frame	–	

Below we briefly present three cases where AI has been applied to support service operations (in particular for predictive maintenance) through the Rebecca platform earlier described.

4.1 Case A

Case A is a public company responsible for the management, maintenance, and administration of the railway infrastructure in Italy. One of the main issues related to this task is to constantly monitor the railway health state and predict the likelihood of faults to implement predictive maintenance and improve safety. The solution, prototyped in Rebecca Builder, made use of real-time data related to different parameters representing railway geometry and collected by an IoT acquisition system. By incorporating information about the warnings generated by operators trained in detecting anomalies, a fault prediction algorithm based on an artificial neural network and XGBoost (a Python module) was implemented and trained for each parameter, allowing to predict the generation of a warning 14 days in advance a possible fault. Through Rebecca Innest, the models were deployed for several lines, and Rebecca Frame was set to send a notification to the maintenance manager whenever the algorithm detects an anomaly in the railway.

4.2 Case B

Case B is one of the leading companies in Europe in the supply, production, and sale of electric power and gas, in the energy and environmental services, and the exploration and production of hydrocarbons. B needed to implement a system to monitor the health status of several assets of an energy production plant (such as gas and steam turbines, heat recovery steam generators, auxiliaries, heat exchangers, condensers, and cooling towers) and to act proactively to reduce management costs, improve plant reliability and optimize the maintenance operations. A monitoring system installed on the plants was responsible for data collection. For each asset, Rebecca Builder was first used to perform data cleaning and then to implement a regression model to predict the output (such as output temperature in the example of the gas turbine modeling) through a feed-forward neural network algorithm. The grid search functionality was used to achieve the best model hyperparameter, and model validation was performed by looking at MAPE metric and control charts, such as the residual and the cumulative sum control charts (CUSUM). The implemented models achieved a precision of over 95% and an MPE < 2%. Through the data experience of Rebecca Frame, the output of the 41 models representing the whole plant could be monitored through dedicated alarms and control charts representing in real-time the difference between the real and predicted output for each asset, thus allowing the operator to spot anomalous system behavior due to possible faults or degradations.

4.3 Case C

Case C is a global leading company for low carbon emission power generation and distribution. C needed to implement predictive maintenance for a wind farm consisting of 18 wind turbines. Using Rebecca Builder, AI models have been built based on 5-years historical monitoring data and maintenance events. Data pre-processing on the dataset workspace showed that 40% of maintenance hours were spent to resolve four machine failure types, thus helping in identifying the most critical components (i.e. generator, slip-ring, and bearing). Model training was carried out with a feed-forward neural network with one hidden layer and the optimal number of neurons was selected through the grid search functionality, by setting the selection criteria based on the lowest MSE. The resulting performance control models were deployed in Rebecca Frame and used to describe the degradation of each component, thus anticipating failures. Control charts were visualized to plot the error between real output value and predict the output value for each component. As an example, the degradation of the slip-ring was characterized by an increasing trend of residuals, up to the time of replacement, thus demonstrating the capability of this model to detect anomalies.

5 Discussion

The description of the three cases focused on the application of AI to the understanding of failure mechanisms and predictions to anticipate maintenance activities. The cases, therefore, allow discussing the purposeful adoption of AI platforms to develop advanced services. All the three companies analyzed provide, through their equipment, services to customers. Case A is in charge of maintaining the railway infrastructure, Case B and C produce energy that is then sold to the customer. The role of AI algorithms in the three cases can be viewed in the light of understanding the functions of the above-mentioned technologies: they provide internal (to the company) and external (to the customer) benefits in a servitization path. In particular, the case applications aim at increasing system availability and safety (from an external viewpoint) and improving service efficiency (from an internal viewpoint). These results are reached by monitoring the systems and component status, understanding and anticipating potential failure, this way improving maintenance planning capabilities on one hand, and reducing maintenance cost and increasing its effectiveness on the other. The case applications are primarily focused on the detection of anomalies and unwanted behaviors in the usage of the equipment, starting from usage data.

6 Concluding Remarks

Among the digital technologies that are increasingly changing the competitive landscape, AI is becoming the new operational foundation of business, defining how the company drives the execution of tasks (Iansiti and Lakhani 2020). It is not surprising therefore that great interest has emerged both in the managerial and academic communities to explore how AI, coupled with more affordable digital technologies, can enable the ongoing strategic transformations in the manufacturing industries, such as servitization. By analyzing three application cases of AI in the domain of product health status assessment and predictive maintenance based on an AI platform, we have investigated the linkages between the adoption of AI digital platform and servitization, therefore advancing knowledge on this topic. In particular, we understand from the cases that companies through the adoption of AI platform achieve external or internal benefits (such as the increase in systems availability or improving service efficiency) through the purposeful exploitation of the functions related to AI platforms.

Moreover, by illustrating the application of an AI platform to three cases, this paper discusses the functions these platforms may have in enabling servitization and what motivates or obstacles their utilization in practice. We conclude that AI platforms can be a fundamental factor in this process since as described above, they enable functions (e.g. data collection, cleansing, normalization, ingestion, selection of the most appropriate algorithms, verification, training, validation, and visualization) by facilitating the manufacturing companies dealing with the top challenges of AI adoption (Goasdaff 2019), such as the need for highly skilled professionals.

Thus, this paper also has implications for managers since they can use the results illustrated to more consciously evaluate the adoption of AI platforms as an enabler of the servitization transformation in their particular context.

Anyway, the research comes with some limitations, mainly related to the fact that our results rely on the application of a specific AI platform, limiting the extent to which the results can be generalized. Future research should thus analyze how different AI platforms in different contexts can be used by companies to servitize their business. Also, more use-cases and a more structured analysis of the results should be considered in order to answer more comprehensively to the research question.

This research appears as one of the first attempts to address the practical implications of AI platforms in servitization, and we hope that this research will inspire other researchers to contribute within this field which we are convinced will significantly advantage both scholars and practitioners.

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