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Artificial Intelligence Operating Model: A Proposal Framework for AI Operationalization and Deployment

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Abstract: At the heart of the new enterprise, across all activities, is a decision factory governed by some kind of intelligence. Among the great promises of Artificial Intelligence (AI) is its ability to lead to a significant evolution in the amount of data received, processed, or generates by companies, particularly those with a digital connotation. To bring about dramatic changes, AI does not need to be science fiction but simply a new way of approaching computerization subjects whether in terms of design, development, or terms of expected results. It should be noted that traditional IT solutions present a form of AI called - Weak AI - while the AI that is the subject of much noise, hype, and promises of transformation and potential for growth is called - Strong AI -. This article aims to present, in a didactic way, a model called D2MO (For Data Ops, ML Ops, Model Ops, and AI Ops) allowing the company to operationalize, in a structured approach, AI subjects, activities, and projects. We target through this article to provide both IT and business experts with a new framework offering a perfect articulation between the different bricks and actors entering into the composition of an AI-based system thus allowing them to operate in harmony and an agile mode while taking advantage of this technology.

Keywords: Artificial Intelligence, ML Ops, AI Ops, Data Ops, Model Ops

Introduction

The leap towards the status of a company with artificial intelligence as a lever for creating value and a catalyst for growth must be accompanied by the deployment, in addition to the necessary prerequisites in terms of human resources, infrastructure, tools, and organizational processes, of a clearly defined operating model and a well-thought-out technology strategy.

The promises displayed by AI do not stop growing over time with a strong promise to transform business models by creating more value and diversifying application fields as shown in Fig. 1 (World Bank, 2020).

Inspired by DevOps best practices, AI operating models are available in hybrid architectures and schemes involving Data, Algorithms, Models, processes, and all the technological bricks necessary for scaling.

A recent study (Martínez-Fernández *et al*., 2021) has highlighted the need and the importance of having a global model for the integration of AI solutions and how the agility process and the permanent collaboration and communication between all teams in charge of the design and the development of AI models and algorithms have made it possible to implement high quality AI solutions.

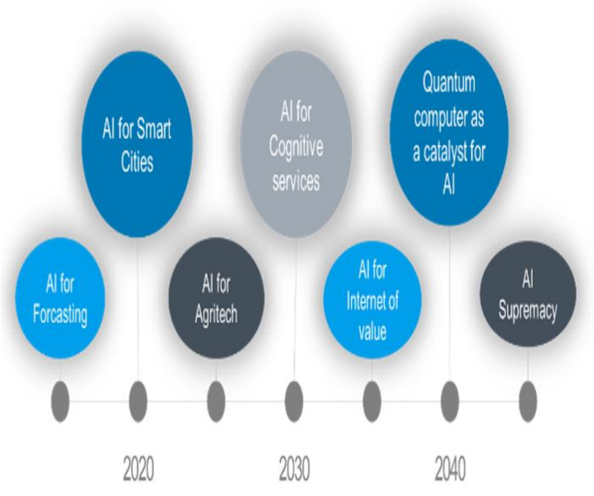

Fig. 1: Timeline of AI innovation over the next 20 years

One of the main motivations of our study is to overcome the lack of pragmatic models to design an operational framework of AI integration and operationalization within the enterprise that will allow the various stakeholders to introduce AI capabilities as a driver of creating solutions and a sure way to increase the intelligence quotient of the organization.

Most companies are indeed very aware of the high potential of AI, but they are stuck in the integration of intelligent components both on the macro level, on the enterprise architecture side, and the technical and operational level for the leap to the augmented Information System. Hence the background of our study, which mainly aims to demystify, in a structured way, the necessary steps to move from a classic operational model that every company masters, to an augmented framework that combines, in the same base, data and intelligence to support the integration of the AI in the transformation journey of businesses and processes within the organization.

Similar studies have tried to address the issue, including the Harvard study "Building the AI-Powered Organization" (Fountaine *et al*., 2019) which pinpointed the organizational and change management prerequisites needed to move to an AI-powered company. Also, the book titled "AI by Design: A Plan for Living with Artificial Intelligence" (Campbell, 2022) illustrates, in a clear way, that for most companies the AI journey consists in making only a sheet which is limited to a representation with milestones and review points. However, the concrete translation on the operational level is subject to several obstacles and ideas that are not at all clear.

Our study tries to complete the reflections with a framework that can be used by any Enterprise to begin its transformation journey towards an intelligent company resourced by the signals emitted from its internal and external data.

The AI operational framework that we propose in this manuscript, called D2MO (For Data Ops, ML Ops, Model Ops, and AI Ops) aims to achieve efficiency gains and economies of scale by drawing on the DevOps best practices guaranteeing orchestration, reliability, agile collaboration, scheduling, and reuse.

Forms of AI

A "Weak AI" factory can already make a series of decisions at different levels of criticality. In some cases, it may manage business information and activities. In other cases, it will guide how the company builds and develops its products. But in all cases, digital decision factories manage processes and contribute to operational decision-making. In this scenario, intelligent solutions are the heart of the business, while humans are moved to the periphery.

On the other hand, the "Strong AI" companies put people back at the center of interest and thus free them from repetitive, useless, or no-value-added tasks. The implementation of this type of intelligence is generally based on the following components:

- Data Pipeline: The semi-automated process that gathers, cleans, integrates, and protects data in a systematic, sustainable and scalable way
- Algorithms: Programs that generate predictions about future states or actions
- Experimentation Platform: Where hypotheses about new algorithms are tested to ensure that their suggestions have the intended effect
- Infrastructure: The systems and components that embed this process in software and connect it to internal and external users and partners

The value at scale generally decreases in weak AI-based models. On the other hand, based on strong AI, value creation can climb much higher. The confrontation between the two types of AI, as shown in Fig. 2, is called a " Collision " point.

As learning and network effects amplify the impact of volume on value creation, businesses built on a digital core can significantly outperform traditional organizations. Collisions are not caused by any innovation in technology or business model. They are the result of the emergence of an entirely different kind of business and they can fundamentally alter industries and reshape the nature of competitive advantage. From this perspective, some studies have classified companies seeking to adopt AI, into five categories (Gerbert *et al*., 2019):

- Stars: Evolve using AI
- Fish: Boost digital and AI maturity
- Question marks: Design and build digital and AI systems
- Cows: Monetize AI performance
- Dogs: Prepare for the jump to AI

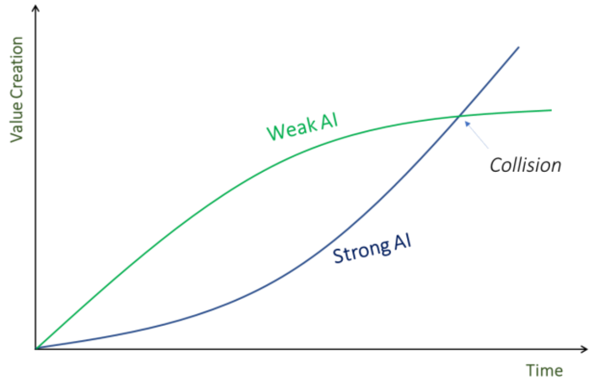

Fig. 2: Value creation: Weak AI vs strong AI

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All the difficulty for the company, therefore, lies in radically transforming its way of adopting AI to maximize the value it can generate while controlling the related risks. This can only be possible through the adoption of a pragmatic approach equipped with a Tool Chain and which will make it possible to support this transition, carry it out in good conditions, and put in place the necessary basics for its success.

Related Works

During our research to propose a model for the automated management of the AIOps process within the company, we confronted our work with some research that tried to answer the problem by relying on different points of view.

Awada *et al*. (2021) proposed a framework based on four main steps:

- Data cleaning
- Selection of features
- Data increase
- Algorithm setting

This study has defined a pragmatic approach to address the issues of supervised ML models and focusing mainly on Data quality. The result of the research has demonstrated that a mastered AIOps approach can improve the process by which a data analyst directs ML systems toward a determined target.

Our model could be in cohabitation with the result of this research because we will try to propose a succinct approach to ensure a better quality of input data to ML models.

Along the same lines, (Caner and Bhatti, 2020) raised the fact that AI-enabled products have automated decision-making capabilities and that AIOps is a rapidly emerging technology and the need for regulation and resolution of issues of ethics are essential elements for the successful implementation of AI within companies. The framework that we will present in this manuscript confirms the great contribution of AIOps and its creative capacity to necessarily focus on the question of ethics. Indeed, our D2MO model will focus primarily on the AI operationalization model and does not address issues related to ethics or the explicability of models. Such subjects can be the topic of future projects, research, and discussions.

Another interesting work (Mikalef *et al*., 2019) tried to develop a theory-based definition of AIOps capabilities and extract the basic resources that compose it. Based on relevant literature, this study has defined and discussed the dimensions and their aspects to realize the business value of investments in AI implementation.

Through our D2MO model, we will demonstrate the relevance of such an approach for the company to be a winner in its AI-based transformation efforts. Certainly, this challenges several Investments and financial efforts of which D2MO will offer a unique channel to supervise, optimize and make more profit.

On another aspect, (Carvalho, 2022) offers a relevant framework for the development of data products, based on a Canvas model that follows the principles of the Agile and Lean methodology. Its main purpose is to serve as a practical tool for generating a roadmap of data products, aligning in a single document the complete view of everyone involved in the real purpose of the project.

The research (McKinsey, 2022) emerges that enterprises often must choose between speed and computational intensity, which can delay more sophisticated analyzes and impede the implementation of real-time use cases. The Framework that we will propose deals with this problem by segmenting the calculation steps and offers the ability of:

- Delegation of calculation to a supercomputer
- The use of the cloud for better resource optimization
- The implementation of a complete business architecture ensures the integration between assets, processes, information, and interventions and allows the identification of new opportunities for the business
- The establishment of mechanisms to make it possible to make the most of the company's data

Finally, (Desai *et al*., 2022) introduced an important concept (product approach) that our research work will facilitate in terms of orchestration and implementation. Indeed, data products can generate impressive returns and rely on existing operational data stores, such as warehouses or Data Lakes. Teams using Data products don't have to waste time finding Data, processing it into the right format, and creating bespoke datasets and data pipelines (which ultimately creates architectural mess and challenges). Our Framework will essentially aim to support this product approach while optimizing design, construction, and above all, deployment efforts for a rich catalog of data-based services.

Results and Discussion

Today, the business world is experiencing a real disruption generated by the increasing volumes of data emanating from vast networks of connected devices which collect and transmit data and information, often in real-time. The way data is generated, processed, analyzed, and visualized for end users is radically transformed by new technologies including Artificial Intelligence and Big Data. Data thus remains an important product to which particular attention must be accorded.

Some research related to the topic of Data and Data Intelligence has focused on the ability to generate a new form of value for the company based on intelligence without necessarily highlighting a global approach that can help organizations to operationalize the model. Indeed, this research has raised the question about the Data Ops and AI Ops capability and the business value that these technologies could bring.

Also, to ensure more efficiency in the implementation of "intelligent" models within companies, the fundamental question to be asked relates to the examination of the capacity of AI to generate value and then to ensure the mechanisms to achieve this objective. Overall, the literature recognizes that AI can produce value in four different ways: Automation, Decision Support, Marketing, and Innovation. By automating many manual tasks, AIOps can enable the human workforce to tackle other activities that require more creative skills, intellectual efforts, and critical thinking.

Although AIOps is still at an early stage of deployment within organizations, it has already become a serious topic of discussion. Indeed, several studies have already examined potential business cases for AIOps and have explored the challenges and opportunities this approach presents. Even though research is still quite fragmented, a consensus is developing around the areas that companies need to consider if they aim to achieve performance gains in terms of process optimization based on DATA.

To ensure a seamless adoption of AIOps, an examination of the factors that contribute to the development and sustainability of its Capabilities within the company must be carried out. This should prevent companies from embarking on costly investments without real competitive or financial repercussions.

The analysis of research related to the subject has shown that a company that uses data from this perspective must adopt automation of the entire chain from collection to dissemination while ensuring that:

- Data is at the center of all decisions
- Data is picked up and processed promptly and ready to use
- Data is considered an information asset that creates value
- The company is always attentive to its ecosystem and ensures the harmonization and continuous update of exchanges with its partners
- Confidentiality, performance, security, and resilience remain at the heart of the Data management process

Any organization wishing to succeed in the challenge of advanced data management must adopt a product approach for better control and better performance of these information assets and its investments around the Data. This new approach provides a set of high-quality Data that people within the organization can easily access and use for different business challenges. This requires a pragmatic Data governance framework. In this sense, some research has focused on the creation of a management framework for managing the Data product approach, to serve as a practical tool for generating a Data product roadmap, aligning in one place the complete view of all people or roles involved in the real purpose of the project.

The main elements of in-depth monitoring in this approach are separated into 3 areas:

- The product vision (including problems, solutions, and assumptions)
- The vision of the strategy (including actors, actions, and KPIs)
- The company's vision (in terms of values, risks, and performance/impact)

In each block, all the discovery necessary to have a unique understanding of each part of the data product that will be developed is explored in detail in the AIOPs universe. Also, each component addresses a key area for correct product planning and development, providing a 360-degree view that spans from troubleshooting to strategic execution, including KPI tracking and risk mapping all by having AIOps as catalysts to feed each Block with useful and relevant information.

On one hand, a Framework presenting a global approach to the integration of AI will undoubtedly make it possible to formalize and harmonize several components entering into the management of the data life cycle and, on the other hand, to generate tangible added value for the company.

D2MO: A Framework for AI Operationalization and Deployment

Experience has shown that most AI projects fail because operationalization is an afterthought. However, the main barrier to scaling AI implementations relate to the complexity of integrating the solution into the existing enterprise applications and IT infrastructure. Indeed, AI-based solutions have struggled to keep pace with the increasing complexity of Information System architectures, the huge amount of data, the diversity of implementations of the platform's hosting solutions (hybrid, on-premise, multi-cloud) and the growing needs in terms of qualified HR skills and competencies.

The focus has always been placed on the development of analytical and conceptual artifacts and Machine Learning (ML) models that cannot be "industrialized" in most cases, instead of aiming upstream for the operationalization of the AI system, by ensuring the development, the continuous delivery and integration of artifacts, translated into products within the company's IT assets.

Several months are generally needed to integrate the ML model into a company's applications asset so that it can produce tangible value. Consequently, the designed framework aimed to operationalize AI systems using, according to a structured approach, different layers, and bricks that are necessary for this operationalization. The biggest challenge is to ensure that all these components can interact with each other in an agile and flexible way while achieving the desired results.

Our operational framework, called D2MO, as presented in Fig. 3, is structured around four components:

- Data ops: Brick reserved for the DATA management in terms of collection, qualification, quality control, processing, distribution, and flow management
- ML ops: Structure reserved for the design, implementation, deployment, and monitoring of Machine Learning models
- Model ops: Refers to a set of control mechanisms ensuring the ML model's governance
- AI Ops: Layer in charge of the integration of the "Intelligence" dimension into the company's value chain

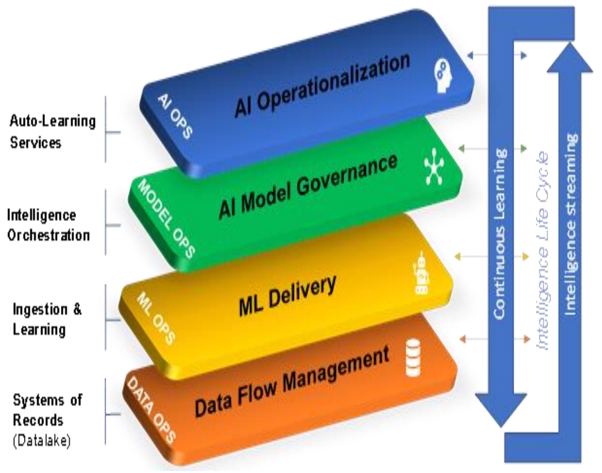

Fig. 3: D2MO framework for AI operationalization: From data to intelligence

A. Data Ops

Companies are aware that Data is a precious mineral that should be exploited to the last seed and to which all the right care must be taken. In that way, they seek usually to take advantage of the opportunities that can be offered by Data. However, they often face difficulties in starting this "new" experience. The question that always arises is "where to start?". The matrix of opportunities offered by data (Kruhse-Lehtonen and Hofmann, 2020), presented in Fig. 4 below, can be used to help the company to identify the subject and to focus on the areas where Data plays the first role in creating value and offering a new form of growth for companies.

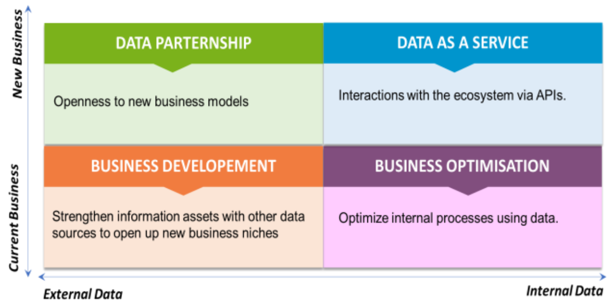

Fig. 4: Data opportunities matrix

Once a solid understanding of data is established within the organization, a data operationalization approach (Data Ops) is required. It is a collaborative data management practice focused on improving communication, integration, and automation of data pipelines within the organization. The objective is to deliver value faster by creating predictable delivery and change management of metadata and all associated artifacts.

Data Ops uses technology to automate the collection, design, deployment, management, and delivery of data with the appropriate levels of governance and management to improve its use and operation in a dynamic environment.

The process of acquiring existing data sources (Keller *et al*., 2020) depends on the type and the source of data and includes downloading data, web scraping, acquiring directly from a sponsor, or purchasing data from specialized aggregators.

Data Ops helps to create, manage and scale data pipelines toward reuse and reproducibility. What is proposed in this component of the model (Fig. 5) is a structuration of the data management process starting with the data collection phase in all its forms (structured, unstructured, or in the streaming form) followed by a qualification phase through the implementation of the necessary modules for cleaning and quality control of the data, before its ingestion and integration into the Company's Datawarehouse/Datalake.

As part of the implementation of the data governing process, the principle of the "4 Cs" is generally used: "Clean, Correct, Coherent, and Complete". However, the world of AI has certain particularities which means that this principle cannot be enough. Indeed, data quality control in the world of AI and Big Data is seen as a correlation between the veracity of the data and the particularities of the context of their execution and utilization (Burgess, 2017).

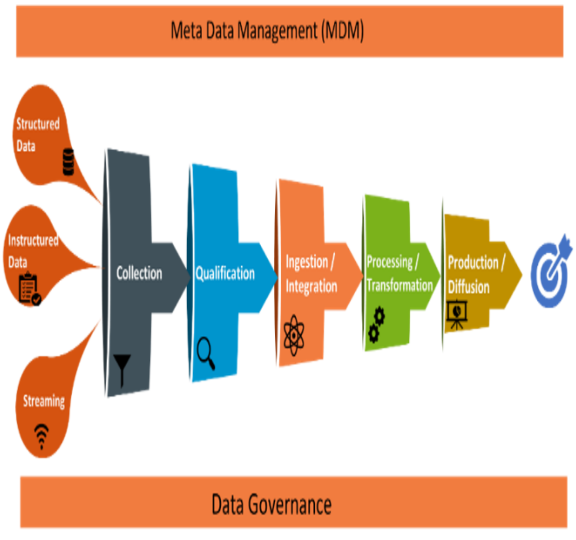

Fig. 5: Data ops: Diagram of the data processing pipeline

When it comes to the ingestion step (Verganti *et al*., 2020), the challenge is to ensure that a wide range of data can be ingested quickly, easily, and continuously. This is an important challenge for model development. Most Data Labs start with manual data extractions and quickly automate the ingestion process so that it can happen regularly (e.g., daily) to ensure that the data available for model development analysis is fresh.

The two remaining steps consist of processing and transforming the data, followed by its production and distribution toward the company's ecosystem. Of course, all these sub-phases must respect the principles of governance and alignment with the company's metadata management repositories.

B. ML Ops

Operationalization of Machine learning programs (ML Ops) aims to streamline the deployment and execution of machine learning models. This brick of the framework supports the publication, activation, monitoring, performance tracking, management, reutilization, maintenance, and governance of ML models.

Traditionally, design activities are human-intensive, but AI is helping to revolutionize this scenario. In the context of ML Ops, the design process (Siddique, 2018) can be fed with real-time data from interactions with customers or with the business ecosystem.

From another perspective, ML Ops aims to standardize the deployment and management of ML models alongside the operationalization of the ML pipeline. Indeed, the Data Engineers are required, first, to stage the data coming from the various sources in a kind of persistent data store for the Data Scientists and then go through the business use cases for learning and testing the dataset while identifying the best algorithm for each business use case. The model is then built and trained through an iterative process resulting in a candidate model.

The model management system acts as a technical component and model exchange channel between Data Scientists and ML Engineers who ensure the deployment of the model in a production environment in collaboration with the developer's team.

It should be noted that ML Ops have evolved (Fregly and Barth, 2021) from their first version which was characterized by the manual creation and deployment of models towards a high level of maturity materializing the third version and where the pipelines are executed automatically either via triggers, following the arrival of new data or the observation of performance issues.

ML Ops also contributes to the collaboration between different roles and responsibilities throughout the development and the operationalization of the machine learning development life cycle steps as illustrated in Fig. 6.

ML Ops helps to establish a sort of framework for the tree following steps:

1. Acquire and integrate data within the company
2. Analyze the data acquired through engineering work while implementing measures and control points to ensure a high data quality
3. Deliver products and solutions representing the added value offered by Machine Learning programs

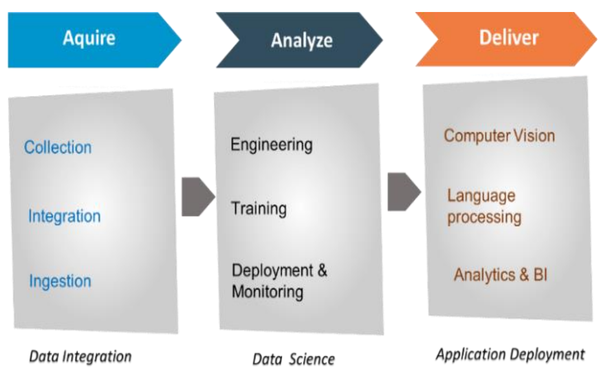

Fig. 6: Machine learning development life cycle

C. Model Ops

Machine learning models are developed in the Labs by Data Scientists, as they go from development to deployment while following appropriate validation and review mechanisms. Comments are thus expressed and exchanged between the interested parties and make it possible to continuously improve the quality and relevance of the models. The most efficient organizations (Siddique, 2018) will try to maximize speed and interactions around this cycle (Fig. 7).

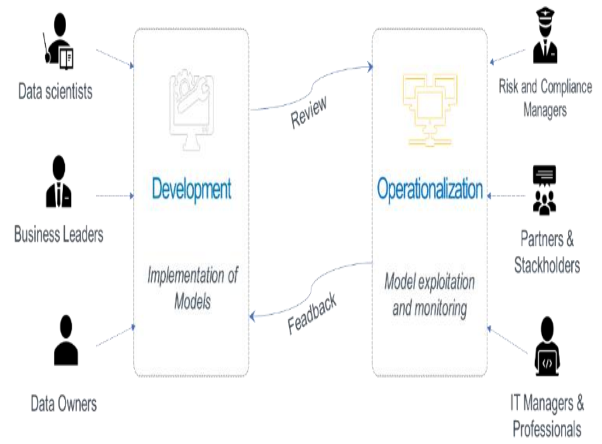

Fig. 7: Machine learning operating models implementation cycle

Model Ops primarily focuses on the governance and lifecycle management of not just ML models, but all AI and decision models that include knowledge, graphs, rules, optimizations, and language models.

Model Ops platforms give business experts the autonomy to interpret results and validate model KPIs. They also offer the possibility to promote or demote AI Models without being dependent on Data Scientists or ML engineers. In that way, Model Ops can help companies facing increasing challenges to scale their analytics and AI initiatives that leverage a combination of statistical and ML models in experimental and production environments.

In the case that this brick is well structured and well thought out, highlighting the KPIs and the control points necessary in the main axes which contribute to the viability and scalability of ML Models (Fig. 8), it offers a high potential to help companies to maximize and scale AI initiatives by providing the necessary level of autonomy and transparency across business, development and operations teams.

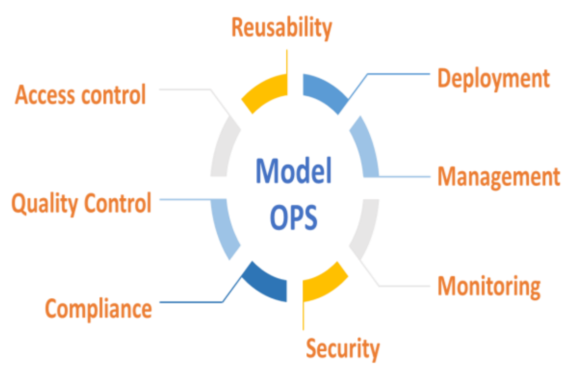

Fig. 8: Principal Axes of control and governance of the model ops

D. AI Ops

Rapid innovations in software architecture and public cloud infrastructures exceed most of the time organization's abilities to monitor and support these complex environments. The most concrete example concerns the financial sector, where the ability to acquire large volumes of data from the corporate environment and process it with artificial intelligence and machine learning significantly modifies the landscape of this strategic sector (Boukheroua *et al*., 2021). In this context, AI facilitates a better ability to predict financial and economic impacts, reach new niches and mitigate risks, reshape financial markets, make risk and compliance management effective, and strengthen prudential supervision.

Some studies (Bogatinovski *et al*., 2021) have focused on the limiting nature of research in the field of AI Ops by qualifying it as an area requiring more structured approaches and procedures. We note also that this subject is becoming the "honey pot" of several researchers and analysts, as shown by the growing number of publications produced and dealing with this theme.

Additionally, the proliferation of cloud-native applications and cloud-based services requires more powerful resources to interpret and apply the ever-increasing stream of data from tools or platforms. Several studies, some of which relate to the telecom sector (El Khatib *et al*., 2019), show the considerable contribution of cloud capabilities to support AI initiatives. Indeed, over the next few years, the most successful organizations will rely on machine learning and artificial intelligence to help them better manage this situation.

This learning put at the service of AI Ops, offers a wide and diversified set of tools for several cases of applications related to many aspects in particular: The provision of effective resources, the planification of complex tasks, and fault management such as anomaly prediction, detection, and correction.

Thus, to successfully operationalize AI models, the focus should be on 6 important axes as mentioned in Fig. 9 and which materialize the AI Ops approach:

- AI Ops tactics: Consists of adopting a pragmatic vision by operationalizing the Data Ops, ML Ops, and Model Ops bricks, prioritizing use cases, and formalizing a roadmap
- Operationalize the models: Relates to the integration of the models in the company's Information System while ensuring the implementation of the necessary control tools and mechanisms aimed at the continuous monitoring of the models
- Extend usage: Analyze the performance of intelligent applications while generalizing and reinforcing use cases
- Integrate robotization: This axis aims to adopt hyper-automation while ensuring the strengthening of internal skills and competencies as also external collaboration and partnerships

- Disrupt traditional systems: Consists of transforming the company's Information System by integrating, gradually, intelligent components
- Mitigate risks: Identify and manage the risks induced using new components, like cyber threats

Furthermore, it should be noted that the operationalization of AI models is certainly an important step, but it is not enough. The hardest part is to keep this operationalization effective and sustainable. In this sense, organizations that have managed to operationalize an AI approach are forced to target a high level of maturity allowing them long-term sustainability and efficiency. In this regard, the level of AI maturity of an organization determines the value it can derive from AI-based solutions. Indeed and although this stage is determined by the combined progression of five organizational dimensions as mentioned in Fig. 10 (Element AI, 2021), each stage shares similar challenges and opportunities that cut across several dimensions.

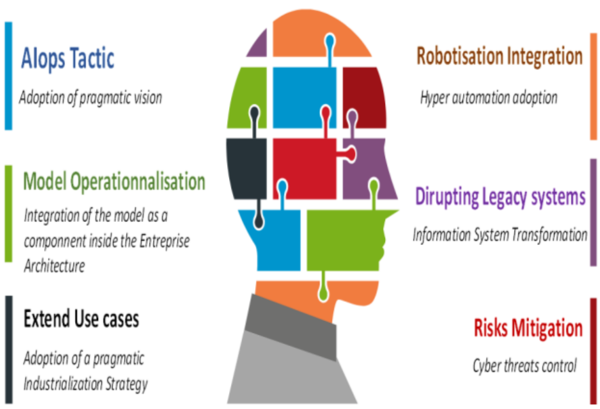

Fig. 9: Diagram of declination of an AI ops approach

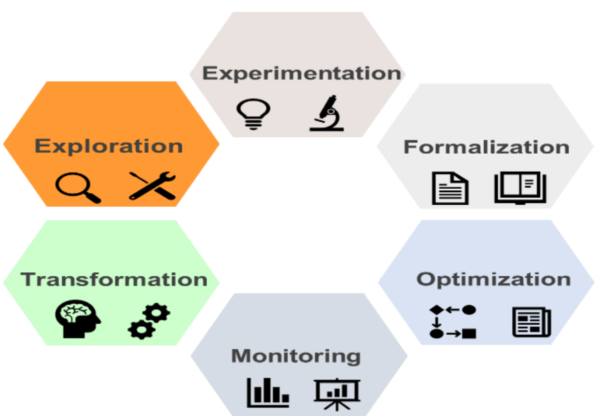

Fig. 10: AI operating model maturity assessment dimensions

Conclusion

The maximization of business value and the achievement of the objectives expected by companies in terms of value creation and the provision of new business opportunities can only be ensured by the implementation of clearly defined operational models providing the company the right capabilities to transform people, technology and processes (IBM, 2020) and enable them to convert, under the right conditions, their business strategies and opportunities into real achievements (Cognizant, 2018).

To bring together all the ingredients that will have to contribute to the successful deployment of this type of model, companies are required to put in place the necessary prerequisites in terms of technological capacities (platforms, infrastructures, and skills) and also in terms of organizational and financial aspects (Lahlali *et al*., 2021).

Also, taking into account their levels of ambition for artificial intelligence adoption and their desire to make the most of it, companies can start from a simple position called "solution acceleration" (Simon and Tuesday, 2019) aiming to find urgent solutions for their business needs towards "AI-Driven" companies where Artificial Intelligence is incorporated into all business processes based on structured models like the D2MO framework, the subject of this article and incorporating the necessary bricks and components for data management (Data Ops), ML model implementation (ML Ops), governance (Model Ops) and finally to their operationalization (AI Ops).

Our study finding allows both business managers and IT leaders to maximize reuse opportunities and to see AI as a "factory" process that is enabled by the D2MO Framework. This new approach is a combination of skills, assets, tools, and processes aimed at improving the efficiency of AI delivery. This will dramatically reduce maintenance and risks. It goes without saying that to succeed, the AI factory needs a blended team of data scientists, and IT and business experts.

Starting an AI journey can be challenging for many enterprises simply because of the resources required and the time taken to demonstrate value. For this reason, our model offers a pragmatic way to start the leap to an intelligent era and to achieve highly valued and tangible outcomes efficiently.

This structured approach often leads companies towards a disruptive era allowing them to "change" the game rules of the industry to which they belong.

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Author's Contributions

Mustapha Lahlali: Carried out the documentary research on the subject, the design, and development of the proposed framework as well as the writing of the first version of the manuscript.

Naoual Berbiche: Carried out the examination of the approach and the results and made remarks, corrections, and additions which enriched the consistency of the research.

Jamila El Alami: Did an overall review of all the research.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that all the other authors have read and approved the manuscript and no ethical issues are involved.

References

Awada, M., Srour, F. J., & Srour, I. M. (2021). Data-driven machine learning approach to integrate field submittals in project scheduling. *Journal of Management in Engineering*, *37*(1), 04020104. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000873

Bogatinovski, J., Nedelkoski, S., Acker, A., Schmidt, F., Wittkopp, T., Becker, S., ... & Kao, O. (2021). Artificial intelligence for IT operations (AIOPS) workshop white paper. *arXiv preprint arXiv:2101.06054*.

Boukherouaa, E. B., AlAjmi, K., Deodoro, J., Farias, A., & Ravikumar, R. (2021). Powering the Digital Economy: Opportunities and Risks of Artificial Intelligence in Finance. *Departmental Papers*, *2021*(024). ISBN-10: 978-1-59806-395-2.

Burgess, A. (2017). *The Executive Guide to Artificial Intelligence: How to identify and implement applications for AI in your organization*. Springer. https://doi.org/10.1007/978-3-319-63820-1

Campbell, C. (2022). *AI by Design: A Plan for Living with Artificial Intelligence*. CRC Press. https://doi.org/10.1201/9781003267003

Caner, S., & Bhatti, F. (2020). A conceptual framework for defining businesses strategy for artificial intelligence. *Contemporary Management Research*, *16*(3), 175-206. https://doi.org/10.7903/cmr.19970

Carvalho, L. (2022). Data Product Canvas - A practical framework for building high-performance data products: How to avoid creating the right solution to the wrong problem?

Cognizant. (August 2018). Building an Effective & Extensible Data & Analytics Operating Model. COGNIZANT 20-20 Insights. page 6.

Desai, V., Fountaine, T., & Rowshankish, K. (2022). A Better Way to Put Your Data to Work. *Harvard Business Review*, *100*(7-8), 151-151. https://hbr.org/2022/07/a-better-way-to-put-your-data-to-work

El Khatib, M. M., Al-Nakeeb, A., & Ahmed, G. (2019). Integration of cloud computing with artificial intelligence and Its impact on telecom sector-A case study. *Business*, *11*(01), 1. https://doi.org/10.4236/ib.2019.111001

Element AI. (2021). The AI Maturity Framework A strategic guide to operationalize and scale enterprise AI solutions. Element AI, page 10. https://www.elementai.com/products/ai-maturity

Fountaine, T., McCarthy, B., & Saleh, T. (2019). Building the AI-powered organization. *Harvard Business Review*, *97*(4), 62-73. http://hbr.org/2019/07/building-the-ai-powered-organization

Fregly, C., & Barth, A. (2021). *Data Science on AWS*. O'Reilly Media, Incorporated. https://www.oreilly.com/library/view/data-science-on/9781492079385/

Gerbert, P., Mohr, J., & Spira, M. (2019). The next frontier in digital and AI transformations. *Boston Consulting Group*. https://www.bcg.com/publications/2019/next-frontier-digital-ai-transformations

IBM. (2020). An operating model for AI at scale How to maximize the expected business value from AI. IBM Research, page 3.

Keller, S. A., Shipp, S. S., Schroeder, A. D., & Korkmaz, G. (2020). Doing data science: A framework and case study. *Harvard Data Science Review*, *2*(1). https://doi.org/10.1162/99608f92.2d83f7f5

Kruhse-Lehtonen, U., & Hofmann, D. (2020). How to define and execute your data and AI strategy. https://doi.org/10.1162/99608f92.a010feeb

Lahlali, M., Berbiche, N., & El Alami, J. (2021). How Enterprise must be Prepared to be "AI First"? *International Journal of Advanced Computer Science and Applications*, *12*(5). https://doi.org/10.14569/IJACSA.2021.0120542

Martínez-Fernández, S., Franch, X., Jedlitschka, A., Oriol, M., & Trendowicz, A. (2021, May). Developing and operating artificial intelligence models in trustworthy autonomous systems. In *International Conference on Research Challenges in Information Science* (pp. 221-229). Springer, Cham. https://doi.org/10.1007/978-3-030-75018-3_14

DOI: 10.3844/jcssp.2022.1100.1109

McKinsey. (2022). The data-driven Enterprise of 2025. https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-data-driven-enterprise-of-2025

Mikalef, P., Fjørtoft, S. O., & Torvatn, H. Y. (2019, June). Developing an artificial intelligence capability: A theoretical framework for business value. In *International conference on business information systems* (pp. 409-416). Springer, Cham. https://doi.org/10.1007/978-3-030-36691-9_34

Siddique, S. S. (2018). *The road to enterprise Artificial Intelligence: A case studies driven exploration* (Doctoral dissertation, Massachusetts Institute of Technology). https://doi.org/10.13140/RG.2.2.34573.44006

Simon, P., & Tuesday, S. (2019). BANKING OVERVIEW - Briefing: How Banks Are Winning with AI and Automated Machine Learning. Data Robot, page 12. https://www.datarobot.com/lp/how-banks-are-winning-with-ai-and-automated-machine-learning/

Verganti, R., Vendraminelli, L., & Iansiti, M. (2020). Innovation and design in the age of artificial intelligence. *Journal of Product Innovation Management*, *37*(3), 212-227. https://www.hbs.edu/ris/Publication%20Files/20-091_3889aa72-1853-42f8-8b17-5760c86f863e.pdf

World Bank. (2020). Artificial Intelligence in the Public Sector Maximizing Opportunities, Managing Risks. International Bank for Reconstruction and Development. page 93. https://openknowledge.worldbank.org/handle/10986/35317