Journal of Management & Technology
e-ISSN: 2177-6652

The AI-Based Leadership Method: fostering symbiotic integration of Artificial Intelligence into management practices

O Método de Liderança Baseado em IA: promovendo a integração simbiótica da Inteligência Artificial nas práticas de gestão

El Método de Liderazgo Basado en IA: fomentando la integración simbiótica de la Inteligencia Artificial en las prácticas de gestión

Como citar:
Monteiro, Wellington R. & Ayrosa, Eduardo A. T. (2025). The AI-Based Leadership Method: fostering symbiotic integration of Artificial Intelligence into management practices. *Revista Gestão & Tecnologia*, vol 25, nº 3, p: 263-285

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"Os autores declaram não haver qualquer conflito de interesse de natureza pessoal ou corporativa, em relação ao tema, processo e resultado da pesquisa"

Scientific Editor: José Edson Lara
Organization Scientific Committee
Double Blind Review by SEER/OJS
Received on 24/08/2024
Approved on 02/01/2025

Abstract

Objective: To present the AI-Based Leadership Method, a novel method for integrating Artificial Intelligence (AI) into Business Management practices, based on the experience of data scientists in large data-driven organizations.

Methodology: Qualitative, using Actor-Network Theory (ANT) as the theoretical-methodological approach.

Originality: The proposed method fills a theoretical gap in the management literature, offering a systematic approach to the symbiotic integration of AI into leadership and management practices.

Main results: Description of a methodology that encompasses the definition of collaborative contexts, the formation of symbiotic teams, the synchronization of knowledge, the automation of supervision, the optimization of decision-making through hybrid committees, and the promotion of a continuous feedback cycle.

Theoretical/methodological contributions: The proposed method offers a future-oriented perspective on promoting a productive partnership between humans and artificial intelligence in the workplace, highlighting the importance of balanced integration of AI into management activities.

Keywords: Artificial Intelligence; symbiotic integration; data science; management.

Resumo

Objetivo: Apresentar o Método de Liderança Baseado em IA, um novo método para integrar a Inteligência Artificial (IA) às práticas de Gestão Empresarial, com base na experiência de cientistas de dados em grandes organizações orientadas por dados.

Metodologia: Qualitativa, utilizando a Teoria Ator-Rede (TAR) como a abordagem teórico-metodológica.

Originalidade: O método proposto preenche uma lacuna teórica na literatura de gestão, oferecendo uma abordagem sistemática para a integração simbiótica da IA nas práticas de liderança e gestão.

Principais resultados: Descrição de uma metodologia que abrange a definição de contextos colaborativos, a formação de equipes simbióticas, a sincronização do conhecimento, a automatização da supervisão, a otimização da tomada de decisões por meio de comitês híbridos e a promoção de um ciclo de feedback contínuo.

Contribuições teóricas/metodológicas: O método proposto oferece uma perspectiva voltada para o futuro sobre a promoção de uma parceria produtiva entre humanos e inteligência artificial no local de trabalho, destacando a importância da integração equilibrada da IA nas atividades de gestão.

Palavras-chaves: Inteligência Artificial; integração simbiótica; ciência de dados; administração.

Resumen

Objetivo: Presentar el Método de Liderazgo Basado en IA, un nuevo método para integrar la Inteligencia Artificial (IA) en las prácticas de Gestión Empresarial, basado en la experiencia de científicos de datos en grandes organizaciones orientadas por datos.

Metodología: Cualitativa, utilizando la Teoría Actor-Red (TAR) como el enfoque teórico-metodológico.
Originalidad: El método propuesto llena un vacío teórico en la literatura de gestión, ofreciendo un enfoque sistemático para la integración simbiótica de la IA en las prácticas de liderazgo y gestión.
Principales resultados: Descripción de una metodología que abarca la definición de contextos colaborativos, la formación de equipos simbióticos, la sincronización del conocimiento, la automatización de la supervisión, la optimización de la toma de decisiones mediante comités híbridos y la promoción de un ciclo de retroalimentación continuo.
Contribuciones teóricas/metodológicas: El método propuesto ofrece una perspectiva orientada al futuro sobre la promoción de una asociación productiva entre humanos e inteligencia artificial en el lugar de trabajo, destacando la importancia de la integración equilibrada de la IA en las actividades de gestión.
Palabras clave: Inteligencia Artificial; integración simbiótica; ciencia de datos; gestión.

Introduction

Departments and organizations that demonstrate a high degree of maturity in using Artificial Intelligence (AI) leverage these algorithms to add value to their operations and decision-making (Davenport & Mittal, 2023; Dwivedi et al., 2021). A data-driven organization acquire and leverage data to create efficiencies, make decisions and develop new products (Fabijan, Dmitriev, Olsson, & Bosch, 2017) – rather than executives always having the final say based on their instincts and experience. It is the data and predictions from machine learning (ML) models that take their place.

ML algorithms are computational products capable of learning and making data-based decisions (Russell & Norvig, 2021). In practice, they analyze large volumes of data to identify and extrapolate patterns and adapt to new circumstances, predicting behaviors (Russell & Norvig, 2021). Data scientists and Business professionals need to curate these data in advance to ensure the quality of the predictions. After all, good predictions need to be built on good data foundations – in the data science field, the saying “garbage-in, garbage-out” reflects such concern (Kilkenny & Robinson, 2018).

Nonetheless, how can we transform the interactions observed between humans and AI, leveraging data scientists’ experience and lessons learned in a data-driven organization, into a Business Management method? Having that said, how can we export and integrate the best practices born from data-driven teams to ensure algorithms’ transformational potential in managerial decision-making? Just as agile methodologies originated in IT and then migrated to other areas such as Logistics, Procurement, and Sales, the same applies to AI.

Literature review

There are open opportunities to better understand the symbiotic relationship between human and AI algorithms in Management by several authors. In fact, Murray, Rhymer, and Sirmon (2021) highlight that future studies should understand when and how AI serves as a coordination mechanism in contemporary organizations and what the suitability of these technologies would be to coordinate specific activities within an organization. Fuller, Hutter, Wahl, Bilgram, and Tekic (2022) noted a gap for future research to study the role of human-machine interaction in Management. Sarlak, Salamzadeh, and Farzad (2020) note that there is a need to plan how AI can be managed within organizations.

In addition to these authors, Hansen and Flyverbom (2015) highlight the opportunity for future studies to explore the consequences for the organization when knowledge is reduced to data that "speaks for itself." Fuller et al. (2022); Pan, Froese, Liu, Hu, and Ye (2022) highlight a need for future research to understand better the impact and changes of AI-based innovation management on developing team competencies and capabilities. Pan et al. (2022) open up the opportunity for future research to discover which factors influence potential alienation and fear regarding using AI as a substitute for humans in organizational tasks.

Borch (2023) notes a sociological interest in AI that has yet to be explored for its potential to transform subjectivity, organizations, and society. Also, Sarlak et al. (2020) note that in the field of Management, there needs to be more research to investigate the link between humans, AI, thoughts, values, resources, and other organizational entities. van Rijmenam and Logue (2021) note opportunities for studies in institutional theories to theorize the agency of AI, including it as an actor within the organization.

Research method

This study uses the Actor-Network Theory (ANT) (Callon, Law, & Rip, 1986; Latour, 2007; Law, 1992) as the theoretical-methodological approach, mainly because of its ability to understand human and non-human actors - in particular, AI algorithms. The use of ANT in this research is justified by its effectiveness in building models and theories (Pollack, Costello, & Sankaran, 2013). There has also been growth in its adoption in organizational studies and other business management subareas (Braga & Suarez, 2018; Oliveira & Valadão, 2017; Tonelli, 2016).

It is, therefore, a qualitative and observational study. The research is carried out by following human and non-human actors by monitoring, describing, and analyzing their relationships - a proposal that is typical of ANT (Latour, 2007; Lee & Stenner, 1999) but which, paradoxically, is seldom explored by studies in management (Lacruz, Américo, & Carniel, 2017). In addition, the research aims to insert itself into the network being studied, effectively participating in the agency of the ANT - a gap in management research (Camillis, Bussular, & Antonello, 2016). The use of ANT in organizational studies allows for new interdisciplinary approaches (Tonelli, 2016) and is especially interesting in studies of organizations that are collaborative, virtual, and innovative (Lacruz et al., 2017).

This document is part of a broader research employing an autoethnographic approach (Adams, Jones, & Ellis, 2015). The contents of the autoethnography were deemed by the authors as too lengthy, considering the size constraints of this paper. Instead, we have chosen to report on the methodological insights gleaned from these autoethnographic findings. This approach allowed us to focus on the participants' lived experiences and perspectives while ensuring the coherence and conciseness of our presentation. The findings from the autoethnography informed our observational strategies and shaped our understanding of the phenomena under investigation, providing a rich and nuanced context for our qualitative analysis.

One of the distinguishing elements brought by this document is the technical experience. One of the authors – who had developed the autoethnography – has actively worked as a data scientist and in information technology roles in the industry for over ten years. In that regard, understanding the technical aspects of AI and how they are used in the industry is crucial to bringing expert knowledge to business management practitioners and scholars. Therefore, this document proposes a management method based on the experiences and learnings acquired from professionals working as data scientists in large data-driven organizations.

Results

This section introduces a practical method applicable to the daily Management activities in organizations that utilize AI algorithms, henceforth named as the AI-Based Leadership Method. Borch (2023) noted a gap for future research to understand how expertise is reconfigured in areas such as management, where ML systems are gaining ground and potentially challenging existing forms of specialization in this area. Moreover, current proposed methods do not focus on the symbiotic relationship between humans and AI – instead, they rely on AI as a tool (Al-Surmi, Bashiri, & Koliousis, 2022; Borges, Laurindo, Spínola, Gonçalves, & Mattos, 2021; Raisch & Fomina, 2023; Trunk, Birkel, & Hartmann, 2020).

This method mitigates the fear of job elimination that can lead humans to avoid providing useful information to AI and, at the same time, considers the synergy between both actors to establish hypotheses and work towards the organizational objectives (Borges et al., 2021). To this end, this method, distilled from the experiences of data science teams in data-driven organizations, consists of seven steps, as follows:

1. Define the Context:
    a. Identify the business process where humans and AI should cooperate.

2. Set Common Goals:
    a. Establish clear, shared Key Performance Indicators (KPIs) between humans and AI.

3. Maintain Symbiotic Teams:
    a. Prioritize task or project-oriented teams over those defined by roles and functions;
    b. Foster teams where AI and humans coexist, maximizing and synchronizing skills;
    c. Assign human technicians to mediate between AI algorithms and other team members;
    d. Designate team leaders with intrinsic technical competencies.

4. Synchronize Knowledge:
   a. Elevate the AI knowledge level of less experienced professionals to prevent incorrect decisions due to technical gaps;
   b. Keep reliable technical documentation as a daily reference for the team;
   c. Humans should learn from insights generated by AI algorithms and vice versa.

5. Automate Oversight:
   a. Implement monitoring standards to ensure AI systems align with set goals, avoiding issues like leakage, data drift, or data and system unavailability;
   b. Ensure monitoring standards are explainable, scalable, and robust.

6. Optimize Symbiosis:
   a. Establish committees for hybrid decision-making and monitoring among managers, human experts, and AI.

7. Feedback into the System:
   a. Maintain open, non-hierarchical communication channels so that both algorithms and humans can report suggestions, difficulties, or observations related to the behavior of AI algorithms.
   b. Implement continuous feedback mechanisms to enhance computational performance and the Data Science metrics of the algorithms and, consequently, the team's performance using them.

The method is named AI-based instead of ML-based. Therefore, this method is applicable in cases employing different forms of AI, such as ML algorithms, computer vision algorithms, speech processing, optimization algorithms, and large language models (LLMs) like ChatGPT.

2.1 Define the Context

The first step fundamentally involves defining a business process where cooperation between humans and AI is necessary. All business processes do not need to involve AI, just as not all require human intervention. For startups and digital organizations, this definition is more apparent. As an example, Human Resources (HR) departments may face daily challenges developing programs, processes, and services that balance the organization's goals with employee needs. Addressing these challenges involves actions such as forecasting, optimizing, personalizing, detecting, and automating decision-making. This step is similar to the *Business Understanding* phase of the CRISP-DM model.

CRISP-DM is an industry-independent process model for data mining (Schroer, Kruse, & Gomez, 2021). Data scientists often use this model and its variants to kickstart a data science project. Before building a new AI, these professionals discuss with business stakeholders to understand whether that problem can or should be best solved with AI.

There are scenarios where an organization or department may not specifically need AI but rather dashboards, adjustments in business management software, or process enhancements. In other contexts, the organization might asymmetrically seek AI algorithms as auxiliary tools for humans without practical cooperation. However, there are cases where the collaboration between AI and humans proves to be the most suitable approach, and it is in this scenario that this method becomes applicable.

For illustrative purposes, let us consider the HR department of a multinational company facing the following challenges:

1. The department struggles to track and interpret employee performance and engagement metrics efficiently;
2. There is a gap between analyzing employee feedback and identifying trends related to organizational climate and job satisfaction;
3. The department faces difficulties in predicting future talent needs, such as the demand for specific skills due to market changes or technological innovations;
4. There are inconsistencies and errors in the data recorded in HR management systems, which hampers strategic decision-making;
5. The department finds it challenging to efficiently personalize development plans and benefits for a large number of employees.

Although these problems represent real use cases, not all require the implementation of AI. For example, implementing interactive visual dashboards could solve the first issue (Ghatak, 2022). The second issue might be addressed through a detailed human analysis of the data or changes in the feedback collection and interpretation processes (Hooi, 2012; Lopes, Lagoa, &

Calapez, 2014). The third issue requires a human analysis of the data or changes in the organizational forecasting processes, as it needs specific insights that an algorithm lacks (Cortes & Forsythe, 2023; Finkelstein Shapiro, Nuguer, & Novoa Gomez, 2024; Turulja, Vugec, & Bach, 2023). Despite involving prediction, ML algorithms predict based on past patterns and may not capture atypical events like the introduction of a new disruptive technology (Russell & Norvig, 2021). The fourth problem can be resolved with improvements in HR management systems to ensure data accuracy, as the issue lies in data entry, not prediction (Whang, Roh, Song, & Lee, 2023).

Finally, the fifth problem is an ideal candidate for applying AI in conjunction with human work. Analysts struggle to personalize plans on a large scale, while AI algorithms require access to data and guidance from analysts to perform such personalization (Russell & Norvig, 2021). Continuous calibrations and monitoring are essential, and pre-processing and post-processing algorithms can be integrated into this approach (Rahman, 2023; Russell & Norvig, 2021). In this context, collaboration between humans and AI is indispensable: humans cannot process the vast amount of data and the speed required for decision-making, making it essential to delegate the production of predictions to AI. Conversely, AI also depends on humans to ensure the continuous quality of its predictions.

Using HR as an example, challenges like personalizing development plans and predicting employee turnover are complex technical tasks beyond a fixed set of rules in a spreadsheet or an enterprise resource planning (ERP) system due to the various attributes available and the possible combinations between them. Furthermore, the information is dynamic, with new employee behavior patterns constantly emerging. In this case, AI is not just a supporting player but a central element in the process: all predictions are made by AI without micromanagement, opposition, or negligence from management. Thus, decision-making is effectively delegated to AI, valuing its speed and efficiency.

2.2 Set Common Goals

Management literature describes a team as a small group of people with complementary skills that will interact and work together to achieve common goals (Schermerhorn &

Bachrach, 2020). By that definition, only humans are taken into account. If only humans are part of a team, then there is no interest in including AI to interact and work together to achieve these goals. This step proposes to consider AI as equal members of a team.

When humans and AI cooperate, this cooperation should aim at specific objectives. Therefore, Key Performance Indicators (KPIs) must be a shared responsibility between both. A KPI that can only be achieved through human intervention is not of interest to AI, just as a KPI that only measures AI performance is irrelevant to humans. For effective and lasting cooperation, KPIs must exist that can be achieved only through the joint effort of humans and AI. Otherwise, they would be indicators that exclusively assess the performance of a traditional human team or just the health metrics of a system. Warner and Waeger (2019) emphasize an opportunity to explore the diffusion of IT and AI algorithms in maintaining transient competitive advantage in organizations.

In this context, metrics like team satisfaction, turnover, or the number of tickets created in the HR system are not necessarily common objectives. For instance, the number of tickets raised in the system may interest human managers, but it does not mean that the work of all business analysts directly contributes to this goal. Similarly, employee turnover may be relevant to the employees and managers but not to the system.

In a department, metrics of exclusive interest to humans, metrics of exclusive interest to algorithms, and shared metrics may exist. For example, the cost of executing algorithms to generate predictions and development plans and the financial amounts related to the savings brought by the algorithms are common objectives between humans and AI in an HR department.

In organizations with many employees, the metric of the cost of running algorithms can be a topic of interest and concern for HR department managers. Just as an industrial production line depends on the efficiency of each stage, with parallel and sequential processes, algorithms in HR follow a similar logic. A delay at any stage can cause significant delays or errors that require immediate action from the on-call team and, in some cases, the involvement of additional team members. In technical teams, concern with mitigating timeout issues is expected, with algorithms typically having a time control that automatically halts calculations if they are not completed within a set deadline.

Moreover, a slow AI algorithm pipeline delays the process of error identification, testing, and adjustments. Therefore, it is in the interest of all analysts that corrections are applied swiftly, allowing them to turn their attention to other projects. For managers, the speed of the pipeline is also essential not only for the reasons mentioned above but also to keep costs under control. The shorter the execution time, the lower the server expenditure, billed by the hour.

Similarly, it is in the algorithms' interest for the pipeline to be fast, as this allows ML algorithms to receive improvements more quickly and provide more robust predictions. Timeout errors also prevent algorithms from delivering their predictions.

The metric of positive outcomes caused by development plans generated by AI or a decrease in voluntary turnover is also shared between algorithms and humans. Both are interested in maximizing the satisfaction of the company and its employees. Algorithms aim to make consistent predictions aligned with the historical baseline and the behavior of each employee. Analysts, in turn, need the algorithms to function correctly to avoid additional efforts in creating new versions. Managers must ensure that the pipeline's collaboration between humans and algorithms is maintained, ensuring its longevity and effectiveness.

Therefore, this method is based on the premise that at least one metric of common interest exists between AI algorithms, human managers, and analysts. If the AI algorithms were removed from the equation, humans would not be able to achieve the goal independently. Similarly, without humans, the algorithms would also be incapable of achieving the same objective independently. It is a departure from legacy management literature where the joint agency between humans and AI impacts organizational routines was not considered (Murray et al., 2021).

2.3 Maintain Symbiotic Teams

The team definition follows the determination of the context and metrics. Here, "symbiotic team" refers to a team where humans and AI are treated with symmetry (Latour, 2007).

Considering the previous examples, an AI algorithm for personalizing career development plans in an HR department has decision-making autonomy, just like the ML algorithms of a fintech, which base their predictions on data prepared by humans.

On the other hand, an ML algorithm that predicts voluntary turnover, used by the HR department to take specific actions for some employees, may have its predictions adopted or not, depending on the human team's confidence in its efficacy. In this case, the algorithm has a peripheral relevance, not being essential to the team's performance of activities.

Therefore, this method applies to the scenarios of algorithms where AI's predictions generate automatic actions, but not in cases where humans analyze and decide whether or not to take action based on the predictions. In this context, AI is seen as a team member, acting, predicting behaviors, and subject to performance variations according to its working conditions. AI is present in team meetings and documents, influencing the work environment and causing stress or discomfort. An interdependence between humans and AI arises: if AI is deactivated, humans cannot perform their tasks; if humans leave the team, AI will deteriorate in quality and effectiveness.

This step is based on the premise that the team should be understood as a symbiosis between humans and AI, requiring symmetrical treatment for both. AI is not just a consultative tool, like in the example of the commodity price prediction algorithm, but an active actor that makes daily decisions. AI is a "worker" who does not take vacations but depends on the support of human colleagues to maintain good performance.

The first step to ensure practical cooperation between humans and AI is to form teams or departments oriented around tasks or projects rather than specific roles or functions. This is similar to the approach of multidisciplinary teams found in agile methodologies (De Smet, 2018). AI pipelines define teams, and contributions are multidisciplinary. When a new pipeline version is developed, the entire team gets involved: data scientists train the models, with co-validation from business analysts. At the same time, data and ML engineers ensure computational performance and robustness.

Having teams focused on AI tasks or projects helps to reduce the distance between humans performing different activities. Moreover, it is essential to consider the symmetry and coexistence between AI and humans. It is not about creating a potential threat to the existence of one or the other (Pan et al., 2022) but about maximizing and synchronizing skills. If humans have creative potential and contextual business knowledge, they should incorporate their insights into the AI construction to maximize algorithmic performance. In the same fashion, parting from the assumption that AI has a high capacity for processing and generalization (Russell & Norvig, 2021), it should be beneficial for the department to share what it has learned with humans, helping to mitigate the risks of spurious correlations or revealing unknown patterns in the data. Thus, humans can adjust the AI, which, in turn, reveals new knowledge to humans using AI explainability techniques, for example (Monteiro & Reynoso-Meza, 2023). In this context, just as managers of human teams need to know the number of people under their leadership and their individualities to optimize performance and minimize conflicts (Schermerhorn & Bachrach, 2020), managers of symbiotic teams should consider algorithms as integral parts of the team. The team thrives when humans and AI develop together: one reflects the other.

Therefore, just as a manager of human teams needs to communicate with their colleagues, negotiate with them, and establish a common language for the exchange of knowledge and execution of tasks, a manager of a symbiotic team must also "talk" with AI algorithms. Interaction is crucial, and understanding is vital. Thus, a symbiotic team requires a manager with technical knowledge. That is, a manager with technical IT experience who has experience implementing, designing, and modifying algorithms, databases, and the technical infrastructure required to support them. Such a manager should be capable of analyzing, approving, and suggesting technical changes, like pull requests, using their technical knowledge. However, this does not necessarily mean that the manager must have a formal IT education but that they have a technical IT career before taking on a leadership role. Consequently, a manager of a symbiotic team must be able to understand the design of the algorithms without the need for a human intermediary. Intermediation in this context can pose risks of simplification, omission, or alteration of information about the essence of the algorithm to the manager.

While the manager of a symbiotic team needs to have the technical ability to interact with humans and algorithms, this requirement does not extend to all team members. Business analysts, data engineers, and some ML engineers may have different in-depth knowledge about ML algorithms than data scientists. Conversely, data and ML engineers often have a firmer grasp of the technical data architecture, which includes pre-processing and post-processing algorithms in a pipeline. In this area, data scientists might not be as well-versed.

Therefore, a symbiotic team also needs an intermediary who can act as a bridge between the AI algorithms and the other human members of the team. This intermediary, a human with strong technical knowledge, must be able to contextualize and explain the algorithms' workings and structure to colleagues with a lower level of technical understanding. This mediation is crucial to prevent alienation through technical opacity (Vredenburgh, 2022): for example, a business analyst who has never programmed an ML algorithm but interacts daily with its predictions must understand how their decisions impact the algorithm and vice versa. Analysts do not need to have a formal education in Data Science. However, they need a human point of contact to contextualize and facilitate their interaction with the AI.

2.4 Synchronize Knowledge

Implementing and maintaining a symbiotic team is fundamental to ensuring symmetry in treating algorithms and humans within the same team. On the other hand, it is essential to recognize that human team members possess varied technical expertise. A team might include data scientists with strong IT backgrounds but need to develop more skills in Statistics, or vice versa. Some data scientists may have extensive academic experience but need more industry experience, or vice versa. Additionally, ML and data engineers may deeply understand the organization's technical architecture, built over an entire career at the same company. In contrast, others may bring diverse experiences from various organizations.

While work is becoming increasingly knowledge-based, the literature often brings knowledge management topics between human team members, and not necessarily between humans and AI (Schermerhorn & Bachrach, 2020). Therefore, for the success of a symbiotic team, there must be a continuous practice of knowledge synchronization between humans and algorithms. Such practice ensures the transmission of context and lessons learned, regardless of the turnover of human members (through hiring, firing, and internal movements) and algorithms (through training, implementation of new versions, and deactivation of old ones).

In data-driven teams of startups, knowledge synchronization is facilitated by meetings and documents. Beyond the typical ceremonies of teams using agile methodologies, there are recurring weekly or bi-weekly internal project alignment meetings where analysts share progress, clarify questions, and consider suggestions from colleagues and managers. Work sessions, whether weekly or ad hoc, are dedicated to solving complex problems with the expectation that everyone contributes to each other's projects. This collaboration is valuable, as all members eventually face complex technical challenges and may need assistance. Understanding and contributing to colleagues' initiatives prepares analysts to respond to technical problems when responsible for on-call duties. There are also scenarios where analysts need to write code to solve complex problems. In these cases, ad hoc "mob programming" (Zuill & Meadows, 2016) meetings are organized, collaborative sessions to share programming techniques, share responsibility for the code, and enhance the quality of technical deliveries.

Meetings are crucial for improving the level of technical knowledge among human analysts. Different technical artifacts are also used to promote knowledge sharing between humans and algorithms. Each initiated project is accompanied by semi-structured documentation, such as architectural decision records (ADRs) and requests for comment (RFC) documents (Bhat, Shumaiev, Hohenstein, Biesdorf, & Matthes, 2020; Rath & Mader, 2020). These documents are accessible to all analysts, allowing different team members to contribute with new comments and questions.

These documents can vary in format, including texts, diagrams, code blocks, spreadsheets, or various electronic file formats. There are no strict rules regarding formatting consistency and standards in documents, prioritizing the reduction of bureaucracy and clarity of the information transmitted (Jansen, Avgeriou, & van der Ven, 2009; Theunissen, van Heesch, & Avgeriou, 2022). This approach makes it easier for new team members or less senior professionals to find the necessary information quickly. Moreover, the use of emails and private messages for knowledge sharing and clarification of doubts is discouraged; instead, all discussions are held in internal enterprise messaging app channels, such as Slack. This allows everyone – including humans who would join the team in the future and LLM solutions like ChatGPT – to access the complete history of discussions through Slack's search functionality.

One of the main objectives of this organization is autonomy. Professionals with little experience or managers not specialized in Data Science can learn from the available documents. Additionally, future team members are expected to understand the context of these documents. This approach aims to ensure that knowledge is accessible and valuable to all team members, regardless of their level of experience or specialization (Rastogi, Thummalapenta, Zimmermann, Nagappan, & Czerwonka, 2017).

Documents specifically detailing AI models also include insights obtained during data manipulation and lessons learned throughout the development of these models.

2.5 Automate Oversight

The next step is to ensure the effectiveness of the work done by humans and algorithms through monitoring. The knowledge exchange between humans and algorithms does not automatically guarantee the correct execution of work. The common objectives defined earlier need to be continuously monitored, and the performance of AI algorithms should not be hidden or obscured.

Therefore, this step involves establishing monitoring standards that ensure the proper functioning of AI algorithms. This includes creating monitoring systems that are easily interpretable by humans in different positions within the team. These monitoring systems consider the daily work of AI algorithms, providing crucial information for managing and continuously optimizing their performance.

The technical paradigm of MLOps addresses the continuous integration and development of AI solutions by technical personnel, such as data scientists and machine learning engineers (Kreuzberger, Kuhl, & Hirschl, 2023). In MLOps, monitoring is also part of these tasks (Kreuzberger et al., 2023). Even though teams can implement this method alongside MLOps practices, this step refers to sharing monitoring standards and business metrics with stakeholders and non-technical humans.

Indeed, there can be two types of monitoring. The first type is proactive monitoring: code that detects anomalies in the data used in the pre-processing algorithms of the pipelines; code that detects deviations in the behavior of the data or the introduction of new behaviors; code that checks if the algorithms are performing their daily work within the predefined time expectations and without errors. These additional algorithms send alert messages on corporate chat applications like Slack or Teams so that humans can interact, track, and correct potential errors. The second type is reactive monitoring: dashboards are created for analysts to obtain additional information about executing the team's ML algorithms. In this way, the algorithms interact with humans and notify them if they need human action to continue performing their work.

2.6 Optimize Symbiosis

Monitoring algorithmic decisions must occur at both operational and strategic levels. The proactive and reactive monitors mentioned earlier operate at the operational level, with analysts and team managers interacting daily with these systems, tracking their development, and implementing corrections when necessary. On-call analysts prioritize problem-solving to ensure the health of the algorithms and the achievement of common objectives, akin to MLOps practices (Kreuzberger et al., 2023). However, senior management may only access these monitors occasionally.

Therefore, the next important step is the implementation of strategic-level monitoring to avoid alienation through technical opacity (Vredenburgh, 2022). It means creating monitoring and hybrid decision-making boards integrating managers, human intermediaries, and AI algorithms. These boards are responsible for approving the development of new algorithms, suggesting changes for new versions of pipelines, adjusting common objectives between humans and algorithms, and monitoring algorithmic decisions in a broader and long-term context.

An example of this is the implementation of monthly monitoring meetings. The focus of these meetings is on presenting statistical metrics and descriptive graphs that reflect algorithmic decisions to the stakeholders (Barker et al., 2023; Hopkins & Booth, 2021). The behavior of the algorithms over the last few weeks is analyzed, comparing it with historical trends. The performance of the most recent pipeline version is evaluated against previous versions to determine its effective performance. Anomalies are technically investigated, with data weighing more than human opinions. However, humans play a crucial role in suggesting improvements and assisting in investigating and correcting errors. The decisions do not exclusively favor the interests of humans or algorithms; both are considered and directly affected by the pipeline.

2.7 Feedback into the System

The last step of the method is the system feedback loop. The joint operation between humans and AI can be at risk if monitors, objectives, and teams are not stimulated and strengthened. For this, there must be central communication channels, open and without hierarchical levels, so that algorithms and humans can report suggestions, difficulties, or points of attention related to the performance of their work together.

In the case of teams operating in a hybrid regime, interactions primarily occur through enterprise messaging applications (like Slack) due to the geographical dispersion of members. These applications support multiple parallel communication channels, each with its specific topics. Various discussions happen simultaneously and evolve throughout the day (O'Meara & Cooper, 2022). Both humans and algorithms participate, sending messages about failures or information of general interest. The use of emails is minimized, preferring shorter and more direct messages in these applications (O'Meara & Cooper, 2022; Simon, 2021). As channels and documents are internally accessible to the entire organization, people with different experience levels and hierarchical positions can contribute. This ensures that information and knowledge are shared freely, without hierarchical filters or team limitations, fostering an open and efficient collaborative environment (Simon, 2021).

Moreover, this step involves establishing technical mechanisms for continuous feedback to improve AI algorithms. It is crucial that AI algorithms not only communicate with humans through established channels but also have effective means for humans to interact with and enhance AI algorithms. Over time, new versions of pipelines and their ML algorithms are not developed from scratch. Instead, corrections and improvements from previous versions are automatically integrated into new versions, and lessons learned in developing old versions are continuously integrated into new ones. Thus, the improvement process is not limited to a list of actions in a meeting minute but is a continuous practice integrated into the development of algorithms.

Conclusion

In this paper, we have introduced the AI-Based Leadership Method, a novel approach designed to enhance the synergy between Business Management practices and artificial intelligence (AI) within organizations. This method, structured around seven key steps, offers a comprehensive framework for integrating AI algorithms into daily managerial activities, fostering a collaborative environment where humans and AI can thrive together.

This proposal distills and summarizes the practices in data-driven organizations from a data scientist perspective. It also considers the opportunities identified in previous research, as well as other methods already proposed. The goal is to provide an actionable, practical method for business management practitioners intending to use AI in their teams based on informed technical knowledge. This informed knowledge is both a highlight and a departure from other business management studies by bringing the domain knowledge and experience from another study area (in this scenario, AI) to management.

Our method begins by defining the context for AI-human cooperation, setting common goals through shared KPIs, and establishing symbiotic teams emphasizing project-oriented collaboration over traditional role-based structures. It prioritizes the synchronization of knowledge across team members of varying technical expertise and advocates for the automation of oversight to ensure AI systems are aligned with organizational goals. Moreover, it emphasizes the optimization of symbiosis through hybrid decision-making and monitoring and champions feedback mechanisms that facilitate continuous improvement.

The AI-Based Leadership Method stands as a testament to the potential of AI in revolutionizing managerial practices. We advocate for a balanced and integrated approach that underscores the importance of mutual understanding and cooperation between humans and AI. This method is not restricted to ML algorithms, extending to various forms of AI, including computer vision, speech processing, optimization algorithms, and large language models like ChatGPT, showcasing its versatility and applicability across different administrative scenarios.

We believe that organizations adopting this method expect improved decision-making processes, enhanced team performance, and a more agile and responsive organization. The AI-Based Leadership Method enables business management practitioners to leverage AI technologies effectively, ensuring that AI and human employees can coexist and cooperate towards achieving common organizational objectives instead of relegating AI to simple tools in an office environment.

References

Adams, T. E., Jones, S. H., & Ellis, C. (2015). *Autoethnography*. New York, Estados Unidos: Oxford University Press.

Al-Surmi, A., Bashiri, M., & Koliousis, I. (2022). AI based decision making: combining strategies to improve operational performance. *International Journal of Production Research*, *60*(14), 4464–4486.

Barker, M., Kallina, E., Ashok, D., Collins, K., Casovan, A., Weller, A., ... Bhatt, U. (2023). Feedbacklogs: Recording and incorporating stakeholder feedback into machine learning pipelines. In *Proceedings of the 3rd ACM conference on equity and access in algorithms, mechanisms, and optimization.* New York, NY, USA: Association for Computing Machinery.

Bhat, M., Shumaiev, K., Hohenstein, U., Biesdorf, A., & Matthes, F. (2020). The evolution of architectural decision making as a key focus area of software architecture research: A semisystematic literature study. In *2020 IEEE International Conference on Software Architecture (ICSA)* (p. 69-80). https://doi:10.1109/ICSA47634.2020.00015

Borch, C. (2023). Machine learning and postcolonial critique: Homologous challenges to sociological notions of human agency. *Sociology*. https://doi:10.1177/003803852.2114.6877

Borges, A. F., Laurindo, F. J., Spínola, M. M., Gonçalves, R. F., & Mattos, C. A. (2021). The strategic use of artificial intelligence in the digital era: Systematic literature review and future research directions. *International Journal of Information Management*, *57*, 102225.

Braga, C., & Suarez, M. (2018, 06). Teoria Ator-Rede: novas perspectivas e contribuições para os estudos de consumo. *Cadernos EBAPE.BR*, *16*, 218-231.

Callon, M., Law, J., & Rip, A. (1986). *Mapping the dynamics of science and technology: Sociology of science in the real world*. Londres, Reino Unido: Palgrave Macmillan UK. https://doi:10.1007/978-1-3.4907.4082

Camillis, P. K. D., Bussular, C. Z., & Antonello, C. S. (2016, 03). A agencia a partir da Teoria Ator-Rede: reflexões e contribuições para as pesquisas em Administração. *Organizações e Sociedade*, *23*, 73-91.

Cortes, G. M., & Forsythe, E. (2023). Heterogeneous labor market impacts of the COVID-19 pandemic. *ILR Review*, *76*(1), 30–55.
Davenport, T., & Mittal, N. (2023). *All-in on AI: How smart companies win big with artificial intelligence*. Harvard Business Review Press.
De Smet, A. (2018). The Agile Manager. *The McKinsey Quarterly*, *3*, 76–81.
Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., ... Williams, M. D. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, *57*, 101994.
Fabijan, A., Dmitriev, P., Olsson, H. H., & Bosch, J. (2017). The evolution of continuous experimentation in software product development: From data to a data-driven organization at scale. In *2017 IEEE/ACM 39th International Conference on Software Engineering (ICSE)* (p. 770-780). https://doi:10.1109/ICSE.2017.76
Finkelstein Shapiro, A., Nuguer, V., & Novoa Gomez, S. (2024). Labor market and macroeconomic dynamics in Latin America amid COVID: The role of digital-adoption policies. *The World Bank Economic Review*, *38*(1), 161–184.
Fuller, J., Hutter, K., Wahl, J., Bilgram, V., & Tekic, Z. (2022). How AI revolutionizes innovation management – perceptions and implementation preferences of AI-based innovators. *Technological Forecasting and Social Change*, *178*. https://doi: 10.1016/j.techfore.202212.1598
Ghatak, R. (2022). Metrics, measurement, scorecards and power of visual intelligence. In *People analytics: Data to decisions* (pp. 175–189). Singapore: Springer Nature Singapore. https://doi: 10.1007/978-981-19-38733 11
Hansen, H. K., & Flyverbom, M. (2015). The politics of transparency and the calibration of knowledge in the digital age. *Organization*, *22*(6), 872 – 889. https://doi:10.1177/13505084.1452.2315
Hooi, L. W. (2012). Enhancing employee satisfaction: an analysis of current promotion practices. *International Journal of Management Practice*, *5*(3), 245–269.
Hopkins, A., & Booth, S. (2021). Machine learning practices outside big tech: How resource constraints challenge responsible development. In *Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society* (p. 134–145). New York, NY, USA: Association for Computing Machinery.
Jansen, A., Avgeriou, P., & van der Ven, J. S. (2009). Enriching software architecture documentation. *Journal of Systems and Software*, *82*(8), 1232-1248. (SI: Architectural Decisions and Rationale)
Kilkenny, M. F., & Robinson, K. M. (2018). Data quality: “garbage in – garbage out”. *Health Information Management Journal*, *47*(3), 103-105. (PMID: 29719995) https://doi:10.1177/1833358318774357
Kreuzberger, D., Kuhl, N., & Hirschl, S. (2023). Machine learning operations (MLOps): Overview, definition, and architecture. *IEEE Access*, *11*, 31866-31879. https://doi: 10.1109/ACCESS.2023.326.2138
Lacruz, A. J., Américo, B. L., & Carniel, F. (2017, 07). Teoria ator-rede em estudos organizacionais: análise da produção científica no Brasil. *Cadernos EBAPE.BR*, *15*, 574-598.

Latour, B. (2007). *Reassembling the social: An introduction to actor-network-theory*. OUP Oxford.

Law, J. (1992). Notes on the theory of the actor-network: Ordering, strategy, and heterogeneity. *Systems Practice*, *5*(4), 379-393.

Lee, N., & Stenner, P. (1999). Who pays? Can we pay them back? *The Sociological Review*, *47*(1 _suppl), 90-112. https://doi:10.1111/j.1467-954X.1999.tb03484.x

Lopes, H., Lagoa, S., & Calapez, T. (2014). Work autonomy, work pressure, and job satisfaction: An analysis of European Union countries. *The Economic and Labour Relations Review*, *25*(2), 306–326.

Monteiro, W. R., & Reynoso-Meza, G. (2023). A review of the convergence between explainable artificial intelligence and multi-objective optimization. *Authorea Preprints*.

Murray, A., Rhymer, J., & Sirmon, D. G. (2021, Jul). Humans and technology: Forms of conjoined agency in organizations. *Academy of Management Review*, *46*(3), 552-571. https://doi:10.5465/amr.2019.0186

Oliveira, V. M. d., & Valadão, J. d. A. D. (2017, 12). Entre a simplificação e a complexidade, a heterogeneidade: Teoria Ator-Rede e uma nova epistemologia para os estudos organizacionais. *Cadernos EBAPE.BR*, *15*, 877-899.

O'Meara, S., & Cooper, C. (2022). *Remote workplace culture: How to bring energy and focus to remote teams*. Kogan Page.

Pan, Y., Froese, F., Liu, N., Hu, Y., & Ye, M. (2022, Mar 26). The adoption of artificial intelligence in employee recruitment: The influence of contextual factors. *International Journal of Human Resource Management*, *33*(6, SI), 1125-1147. https://doi:10.1080/09585192.2021.1879206

Pollack, J., Costello, K., & Sankaran, S. (2013). Applying actor-network theory as a sensemaking framework for complex organisational change programs. *International Journal of Project Management*, *31*(8), 1118 – 1128. https://doi:10.1016/j.ijproman.2012.12.007

Rahman, A. (2023). Data collection, wrangling, and pre-processing for AI assurance. In *AI assurance* (pp. 321–338). Elsevier.

Raisch, S., & Fomina, K. (2023). Combining human and artificial intelligence: Hybrid problem solving in organizations. *Academy of Management Review*(ja), amr–2021.

Rastogi, A., Thummalapenta, S., Zimmermann, T., Nagappan, N., & Czerwonka, J. (2017). Ramp-up journey of new hires: Do strategic practices of software companies influence productivity? In *Proceedings of the 10th Innovations in Software Engineering Conference* (p. 107–111). New York, NY, USA: Association for Computing Machinery. https://doi:10.1145/3021460.3021471

Rath, M., & Mader, P. (2020). Request for comments: conversation patterns in issue tracking systems of open-source projects. In *Proceedings of the 35th Annual ACM Symposium on Applied Computing* (pp. 1414–1417).

Russell, S. J., & Norvig, P. (2021). *Artificial intelligence: A modern approach*. Hoboken, Estados Unidos: Pearson.

Sarlak, M. A., Salamzadeh, Y., & Farzad, F. S. (2020). *Actor-network theory and networked organizations, proposing a conceptual framework* [Book chapter]. Springer. https://doi: 10.1007/978-981-15-7066-711

Schermerhorn, J., & Bachrach, D. (2020). *Management*. Wiley.

Schroer, C., Kruse, F., & Gomez, J. M. (2021). A systematic literature review on applying CRISP-DM process model. *Procedia Computer Science*, *181*, 526–534.

Simon, P. (2021). *Reimagining collaboration: Slack, Microsoft Teams, Zoom, and the post-COVID world of work*. Motion Publishing.

Theunissen, T., van Heesch, U., & Avgeriou, P. (2022). A mapping study on documentation in continuous software development. *Information and Software Technology*, *142*, 106733.

Tonelli, D. F. (2016, 06). Origens e afiliações epistemológicas da Teoria Ator-Rede: implicações para a análise organizacional. *Cadernos EBAPE.BR*, *14*, 377-390.

Trunk, A., Birkel, H., & Hartmann, E. (2020). On the current state of combining human and artificial intelligence for strategic organizational decision making. *Business Research*, *13*(3), 875–919.

Turulja, L., Vugec, D. S., & Bach, M. P. (2023). Big data and labour markets: A review of research topics. *Procedia Computer Science*, *217*, 526–535.

van Rijmenam, M., & Logue, D. (2021). Revising the 'science of the organisation': theorising AI agency and actorhood. *Innovation: Organization and Management*, *23*(1), 127 – 144. https://doi:10.1080/14479338.2020.1816833

Vredenburgh, K. (2022). Freedom at work: understanding, alienation, and the ai-driven workplace. *Canadian Journal of Philosophy*, *52*(1), 78–92.

Warner, K. S. R., & Waeger, M. (2019, Jun). Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal. *Long Range Planning*, *52*(3), 326-349. https://doi:10.1016/j.lrp.2018.12.001

Whang, S. E., Roh, Y., Song, H., & Lee, J.-G. (2023). Data collection and quality challenges in deep learning: A data-centric AI perspective. *The VLDB Journal*, *32*(4), 791–813.

Zuill, W., & Meadows, K. (2016). Mob programming: A whole team approach. In *Agile 2014 Conference, Orlando, Florida* (Vol. 3).