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INSIGHTS FROM THE INTEGRATED METHODOLOGICAL FRAMEWORK FOR AI PROJECT DEVELOPMENT

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ABSTRACT
The present research addresses the context of the design, management and development of AI systems that involve multiple issues and unique challenges. Because the AI world is a multidisciplinary field that involves concepts of computer science, statistics, mathematics and specific knowledge of data science, in addition to the necessary care with ethics and privacy. It aims to propose a comprehensive and flexible methodological framework for the entire development cycle of AI systems, which fills the existing gaps in traditional approaches by integrating: best project management practices, advanced artificial intelligence techniques, ethical, legal, transparency and privacy considerations, alignment with corporate strategy initiatives, collaboration and customer experience, adaptability and continuous value generation for the business, in different organizational contexts.

Keywords: Design, Development, KPI, AI, Methodology.

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INTRODUCTION

Artificial intelligence (AI) has emerged as a vital research field in the age of digitalization, with the potential to facilitate growth and progress in a challenging way across multiple domains.

In fact, AI has been transforming various sectors and processes by providing innovative and rapidly implemented solutions to complex issues in an innovative way. The pace of change continuously at a speed never before observed (Dwivedi *et al.*, 2021). However, the challenge of a successful implementation of an AI project requires a systematic and integrative approach.

In this way, Ng (2017) highlights: "The central purpose of AI activity is to reduce the gap between what AI can do and what users need". This underlines the importance of managing stakeholder expectations and integrating AI systems into existing workflows, as there is often a gap between what AI can realistically achieve and what project stakeholders expect it to achieve.

It is up to managers to structure and maintain multidisciplinary teams with skills in data science, machine learning, software engineering, and knowledge and experience in the business area in compliance with regulations and legal aspects. As a central element, it seeks to meet the integration of AI systems with existing workflows and processes with the appropriate human-machine interface (Ebert; Duarte, 2018).

On the developers' side, it requires meeting the requirements of data quality and availability, model selection and tuning, system scalability, and deployment processes according to Dean (2020): "In machine learning, you want to align people and data" in order to keep up with the rapid evolution of resources in the field of AI and continuously update your skills. Thus, Müller *et al.* (2024) recalls the rapid evolution of technology and the increasing complexity of data have created new challenges, including the difficulty in maintaining data consistency and quality throughout the entire project lifecycle.

Designing, managing, and developing AI systems present unique challenges. Solutions must not only solve complex problems, but also ethically and impartially guide the processes and developments throughout the project. An AI system must also be transparent and easy to understand and reproduce. AI is a multidisciplinary field that involves concepts of computer science, statistics, mathematics, and specific knowledge of data science, in addition to the necessary care with ethics and privacy. The available

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methodologies are not complete or do not comprehensively address these contemporary challenges.

The significant advances in AI project management methodologies contrast with several limitations as per Brendel *et al.* (2021), where traditional methodologies do not keep up with the pace of technological change and business requirements. In addition, the challenge of integrating ethical factors and the necessary transparency in all phases of the project is a significant barrier.

JUSTIFICATIONS

The most widespread and used methodologies for projects for the development of artificial intelligence systems (CRIDSP-DM; OSEMN; SEMMA; KDD) do not provide adequate solutions to the current challenges of projects of this nature. A new methodological structure is needed, modern and adherent to this challenging scenario, which fills the needs not met by the existing gaps in the methodologies and approaches in use.

We can highlight some recent market cases where there was a bias of discrimination, lack of ethical considerations, and violation of the privacy rights of individuals, due to non-integrative approaches and without considering all the necessary nuances:

Amazon faced a gender bias problem in its AI-based recruitment tool, where the analysis penalized resumes of female candidates because the trained model was loaded with historical data where the presence of male employees predominated (Köchling, Wehner, 2020).

The Google Photos app mistakenly labeled some black people as gorillas due to the lack of inclusion of diversity in the mass of training data for the artificial intelligence-based system (Garcia, 2016).

IBM developed Watson for Oncology to assist physicians in treating cancer that offered inadequate or unsafe recommendations due to a lack of robust training based on more careful and validated clinical analysis (Strickland, 2019).

Microsoft has developed a game on Twitter to learn interactively from users. Within hours of launch, the app had absorbed and was using offensive, malicious, and inappropriate messages due to the toxic behavior of some users (Neff, 2016).

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While there are *frameworks* that address technical and management aspects, few offer clear guidance on how to incorporate these ethical principles in a practical and effective way (Badmus, 2023). The most widespread and used methodologies for artificial intelligence projects (CRIDSP-DM; OSEMN; SEMMA; KDD) do not provide adequate solutions to current challenges. Issues such as adaptability, reproducibility, ethics, management, validation of results, and continuous value generation are often not met.

According to Ajiga, Okeleke, Folorunsho (2024), high-tech companies can adopt methodologies that respond to market changes and deliver high-quality software products by establishing robust governance structures that meet the complexity of the models and ensure data privacy and security.

Steidl, Felderer, Ramler (2023) also highlight the need for the *pipeline* for building and implementing artificial intelligence systems to be adaptive, with continuous improvement in the aspects of data manipulation, machine learning, systems development, and product operation.

According to Nieto-Rodriguez (2021), the failure rate in projects is still extremely high due to pressures from market trends, including automation, sustainability, diversity, and inadequate management with little visibility of the project situation, which encourages the need to create a format to meet these demands, providing projects with purposeful management, adaptability, and a focus on delivering results with value generation.

This review of the methodologies for developing AI project systems is a valuable exercise, instrumenting organizations and their professionals in choosing the most appropriate approach for the management of their specific AI projects, also highlighting the constant need for innovation and adaptation in the face of the continuous evolution of AI technology. It is therefore justified to propose a new solution that will meet the needs not covered by the existing gaps in the methodologies, approaches and methods available.

OBJECTIVES

This research project proposes the creation of a comprehensive and flexible methodological framework for the entire development cycle of AI systems, which fills the gaps existing in traditional approaches by integrating: best project management practices, advanced artificial intelligence techniques, ethical, legal, transparency and privacy considerations, alignment with corporate strategy initiatives, collaboration and customer experience, adaptability and continuous value generation for the business, in different organizational contexts.

In order for the main objective to be achieved, the specific objectives will be worked on, as follows:

- Critically analyze current methodologies for developing AI projects, highlighting existing gaps in relation to contemporary needs;
- Identify essential requirements for a comprehensive, flexible and integrated methodology for developing AI projects;
- Proposal of a methodological structure that covers all the necessary requirements to meet the identified needs;

Thus, the present research seeks to address and identify the scarcity of a comprehensive design methodology for the development of artificial intelligence systems that meets emerging challenges, especially the aspects that configure gaps in the methodologies and approaches in use: the adequate treatment and quality of data; ethical, legal, privacy, and security considerations; the monitoring and control of the AI project throughout the development cycle; the application of innovative artificial intelligence technologies; adaptability and direction for the best customer experience; and the continuous generation of value for the business.

METHODOLOGICAL PROCEDURES

Initially, there is bibliographic research with consultations to specialized publications in books, periodicals, scientific articles and websites focused on the subject in question that are relevant and chronologically.

The present research is of an applied nature based on the knowledge and technologies available to generate products or processes aimed at the analysis, discussion and possible solution of specific problems (Lakatos, Marconi, 2021).

Nevertheless, it seeks *insights* from new methodologies for the development of AI systems to be tested for their applicability through feedback, KPIs (*Key Performance Indicators*) in the process of analyzing results and successive refinements based on metrics.

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Ethical and privacy issues will be considered during the conduct of this research project, in accordance with Brazilian legislation, such as the LGPD (Brazil, 2018), preserving the security and confidentiality of data.

CONCEPTUAL REVIEW OF THE STATE OF THE ART

The management of projects involving Artificial Intelligence concepts requires specific practices due to their complexity and iterative nature. Traditional frameworks such as CRISP-DM, OSEMN, SEMMA, and KDD provide a foundation for structuring the process, from data collection to the implementation and evaluation of the models (Firas, 2023).

The CRISP-DM (*Cross-Industry Standard Process for Data Mining*) methodology, created about two decades ago, Martínez-Plumed, Contreras-Ochando, Ferri (2021) highlights the most used standard for the development of solutions that encompass data science, especially for process-oriented projects. However, they reinforce that in projects that require exploratory analysis, there is a need for greater flexibility and monitoring of time and costs.

Projects involving data science see many challenges to be overcome to ensure their effectiveness and not generate ambiguous results. The application of adaptive project development approaches, such as SCRUM and KANBAN, allows for incremental deliveries, but requires some other methodology combined with this agile process, which avoids endless iterations and the non-continuous generation of value, culminating in customer dissatisfaction (Amirian, Abdollahzadeh, Sulaiman, 2024). They also identify that the Agile-SCRUM approach allows time-bound iterations (*sprints*) and generates incremental deliveries, but that this depends exclusively on a small group of people and, sometimes, on a single individual: the *Product Owner*. And they suggest the use of the CRISP-DM methodology combined with this agile process to avoid endless iterations, without generating value and customer dissatisfaction.

On the other hand, the OSEMN (*Obtain, Scrub, Explore, Model, and iNterpret*) methodology created in 2010, is not intended to evaluate ethical, privacy, project control, or customer experience aspects. The focus involves the technical aspect of handling large volume data and machine learning (Kumari, Bhardwaj, Sharma, 2020).

The SEMMA (*Sample, Explore, Modify, Model, Assess*) methodology developed by SAS (Abell, 2014) technically acts on the machine learning model, constituting a proprietary solution applicable to data mining processes in the company's own tools, without focusing on business issues.

The KDD – *Knowledge Discovery Database* approach was created in the 1990s and represents a technique used in *Data Mining* (Fayyad, Piatetsky-Shapiro, Padhraic, 1996). Its focus is also concentrated on the transformation and treatment process – the so-called *data flow* pipeline.

The implementation of AI projects faces numerous challenges ranging from technical complexity to managing stakeholder expectations. One of the main challenges faced in implementing AI projects is the need to align technological capabilities with strategic business needs. Often, this disconnect results in solutions that, while technically feasible, do not fully meet organizational objectives (Shang; Low; Lim, 2023).

Additionally, AI project management requires the coordination of multidisciplinary teams and the integration of advanced technologies such as machine learning and natural language processing. Without a clear methodology, these challenges can lead to failures to meet deadlines and budgets, or even to the delivery of results below expectations *(*Taboada *et al.,* 2023).

Aldoseri, al-Khalifa, Hamouda (2023) highlight that data quality and availability are often critical factors limiting the success of these projects. In addition, the integration of multidisciplinary teams, which include data scientists, software engineers, and business domain experts, presents significant challenges to project cohesion.

Other issues such as ethics and transparency in AI have gained prominence in the literature, with a focus on the need for AI systems that are not only technically sound but also socially responsible. Recent literature, such as the work of Palumbo, Carneiro, Alves (2024), has identified the lack of objective metrics to assess ethics in AI, which makes it difficult to implement ethical practices consistently.

Additionally, the implementation of ethical guidelines, such as those proposed by the IEEE and the European Union, has been advocated as an essential step to ensure that AI systems are fair and accountable. However, the practical application of these guidelines still faces challenges, particularly in balancing transparency and intellectual property protection or data privacy (Cappelli; Serugendo; Woodgate; AjMeri, 2024).

Through Saltz's experiment, Shamshurin and Crowston (2017) demonstrated the limitation of existing project management methodologies with adaptive approaches to address processes involving artificial intelligence projects.

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For Firas (2023), the process of implementing data analysis projects, technical barriers, and lack of structured approaches are a major challenge. It thus suggests the adoption of Formal Concept Analysis (FCA) in the construction of knowledge and in support of data mining. In this way, he suggests the combination of the SEMMA and CRISP-DM methodologies in an effective strategy.

Lahiri and Saltz (2023) discuss the need to ensure ethical principles during the development of AI projects, minimizing risks and, thus, facilitating the viability of projects. They propose collaborative surveys using SCRUM or Data-Driven Scrum to validate projects before their implementation.

Jobin, Ienca and Vayenna (2019) also reinforce the need for AI projects to follow the ethical principles of: transparency; fairness and impartiality; non-maleficence; responsibility and privacy.

On the other hand, Vanegas, Mejía, Agudelo, *et al.* (2023) propose the incorporation of principles from the Essence theory in the application of the CRISP-DM methodology to improve the understanding of the essential, common, and universal elements of software design and use best practices to generate the expected results.

According to Boudreau (2024), a large percentage of projects involving data science are failing and a new project management approach is needed to ensure traceability, reproducibility, and knowledge retention throughout the project development cycle.

The gaps identified in these methodologies prevent the generation of more satisfactory results in the development of artificial intelligence projects. This review of existing AI design methodologies represents a crucial stage in understanding the current scenario. In addition, this diagnosis provides valuable insights for the development of new approaches, more appropriate to contemporary business needs.

The traditional software development cycle, the so-called SDLC (*Software Development Life Cycle*), represented in Figure 1, provides for data input and an automated logical process (with pre-defined rules processing) that generates a desired output. The construction of the solution requires programming in a certain language, whose commands interpret the rules provided and, from the data entered, generate the answers in the output of the system.

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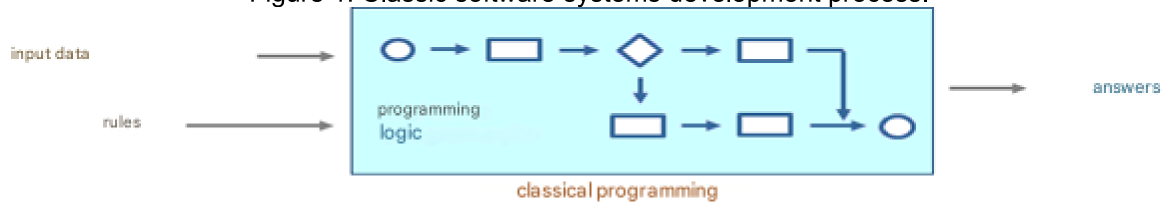
Figure 1: Classic software systems development process.

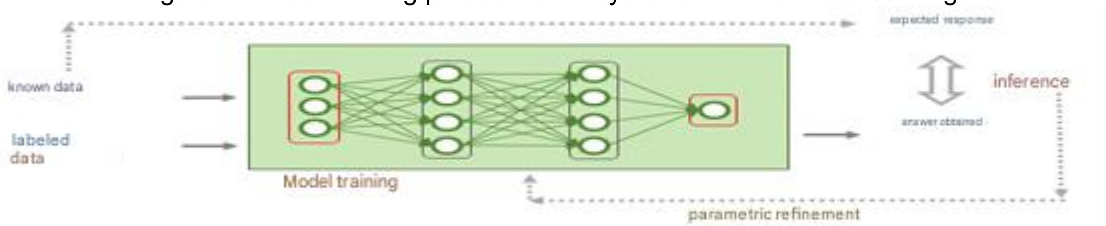


Source: The author

The most common systems involving artificial intelligence use machine learning, through neural networks, where the input of data is compared with the output results, applying weights to variables that associate this data with each other (Davenport, 2018). In this case, two construction steps are required:

- First, we need to create and train a model from data that will be used as a reference to obtain an expected result (Figure 2). Iterations with parameter adjustments are applied in a process of feedback and cyclic refinement of the model, until an accuracy and precision appropriate to the purpose of the application is achieved in a process called result inference.

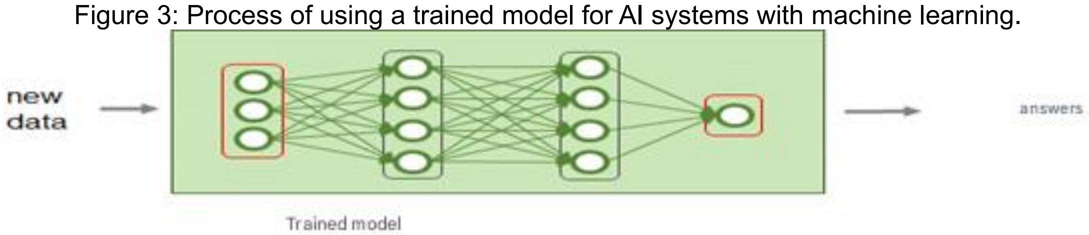
Figure 2: Model training process for AI systems with machine learning.



Source: The author

- Then, this trained and adjusted model will be able to receive general data and produce the requested answers (Figure 3).

Figure 3: Process of using a trained model for AI systems with machine learning.

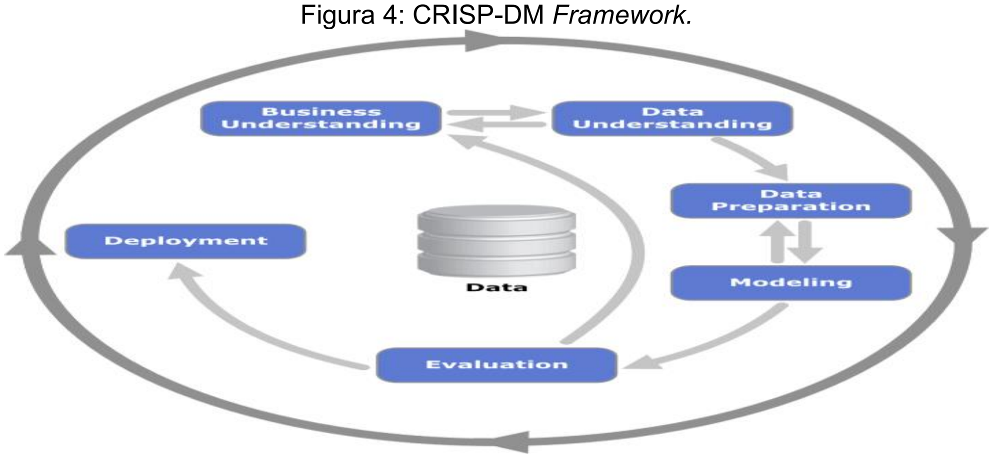


Source: The author

The following are the most commonly used methodologies in the development of artificial intelligence systems, commenting on their contribution and the challenges and obstacles in relation to their applicability.

The CRISP-DM (Cross-Industry Standard Process for Data Mining) methodology demonstrated in Figure 4 stands out as one of the oldest and most widely used methodologies in the field of data mining and machine learning. It was established in 1996 with the aim of providing added value to DaimlerCrysler's customers through data mining specialists, who could rely on a defined standard for their activities. However, this methodology does not address the issues of ethics and privacy (Jobin, Ienca, Vayenna, 2019) and control of the quality, time, and cost of the project (Ferreira, Da Silva, *et al.*, 2018).

Figura 4: CRISP-DM *Framework.*



Source: Chapman, 2000

Data scientists, for the most part, conduct their different types of projects through a similar workflow. A popular representation of this workflow is called OSEMN (Hotz, 2024).

Created in 2010, OSEMN (*Obtain, Scrub, Explore, Model, and iNterpret*), represented in Figure 5, also does not deal with aspects of ethics, privacy, project monitoring, and customer experience. The focus continues on the technical functions of handling high-volume data and machine learning.

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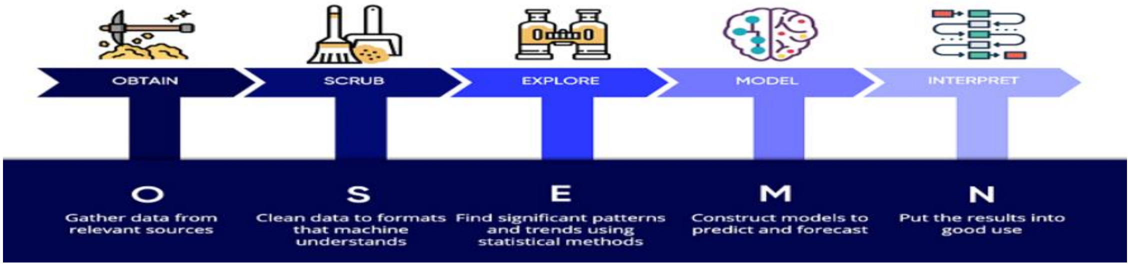
Figure 5: OSEMN Framework.

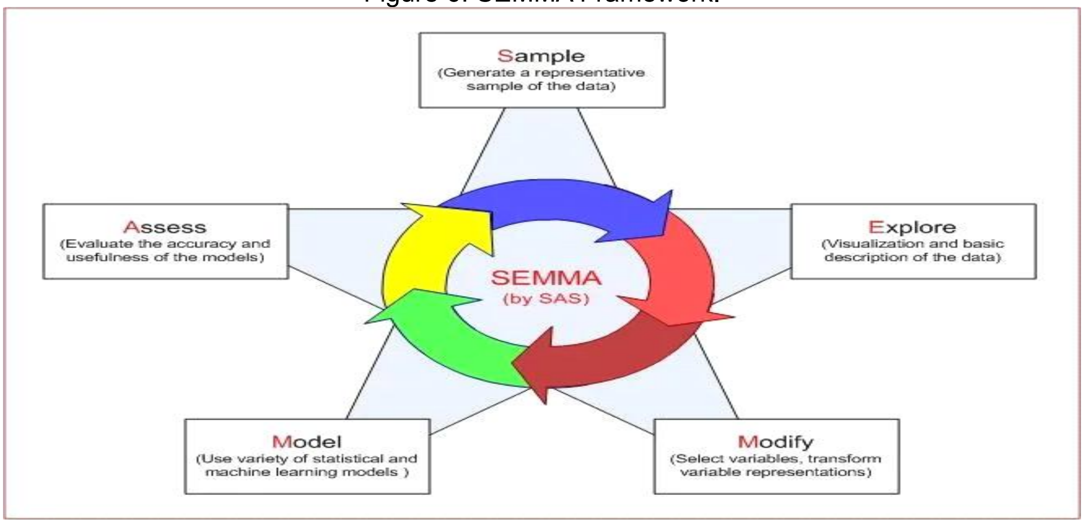


Source: Kumari; Bhardwaj A Sharma (2020)

The SEMMA methodology, with its five stages: sampling, exploration, modification, modeling and evaluation (*Sample, Explore, Modify, Model, Assess*), is represented in Figure 6.

According to Firas (2023), these stages focus on modeling for data mining, and do not address business issues. This option was developed as a proprietary solution to optimize the data mining process in the SAS company's tools, which limits its use due to the dependence created around its supplier.

Figure 6: SEMMA Framework.

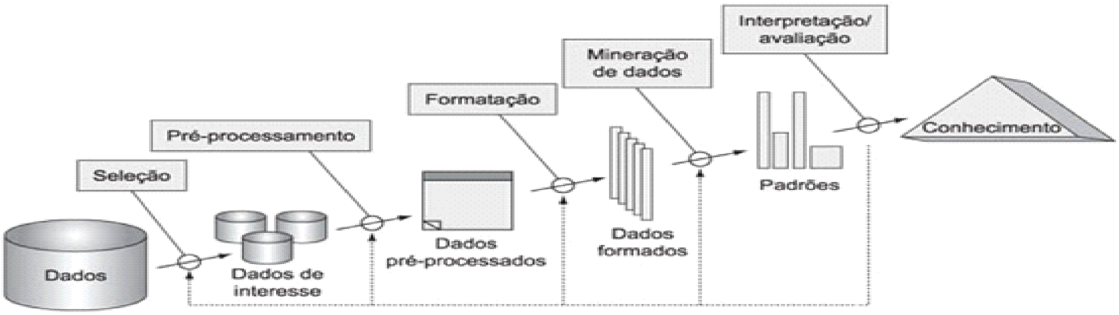


Source: Abell (2014)

Another, even older approach, the Knowledge *Discovery Database (KDD*), shown in Figure 7, was created in the 1990s for the preparation and interpretation of information on a large volume of data and represents a technique widely used in Data Mining.

According to Azevedo, Santos (2008), some efforts were made in the industry to obtain an industrial standard and a sequence of steps that would guide data mining. However, this approach does not focus on business issues, but rather on the process of the *data flow pipeline* and its treatment to obtain *insights*.

Figura 7: Knowledge Discovery in Databases (KDD) Methodology.



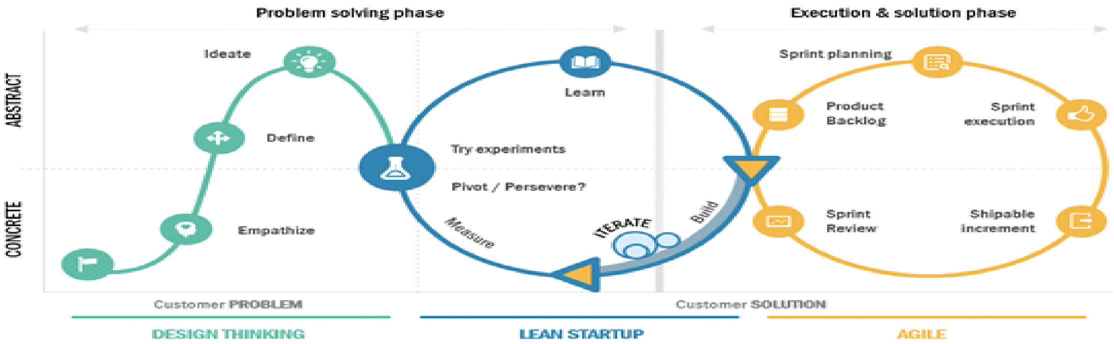
Source: Fayyad *et al.* (1996)

The need to adapt quickly to change and continuously generate value requires the application of successful practices that meet business challenges in a timely manner (Project Management Institute, 2021).

According to Pradeep (2021), the combination of specific methods and approaches applied at each stage of a project's development lifecycle can aid in its success (Figure 8). In this model, the author presents a proposal with three well-defined stages, where the application of tools, methods, approaches and methodologies described below are suggested:

- Phase 1: use of *Design Thinking* to facilitate the creation of ideas based on empathy, definition and clear discussion of the problem with project stakeholders;
- Phase 2: transformation of the best ideas into business models for testing, prototyping, experiments, simulations, until a lean solution can be designed, applying the *Lean Startup* to keep the focus on the expected result (effectiveness) of the process;
- Phase 3: Efficient construction (focus on productivity) and incremental product deliveries (in *sprints*) quickly and adaptively, with the best practices of agile management.

Figure 8 – Combination of *Design Thinking, Lean Startup and Agile* in Project Management.



Source: Pradeep (2021).

THE RESULTS, THE PROPOSITION AND ITS IMPACTS

The comparison between existing methodologies for AI projects reveals itself as an essential analysis to understand the evolution and progress in the field of AI. Traditional methodologies, such as those mentioned here (CRISP-DM, OSEMN, SEMMA, KDD) widely used for decades, demonstrate effectiveness in data mining and machine learning projects. However, given the rapid advancement of AI technology, there is a need for new approaches, more adaptable to current demands and impositions, such as ethical and transparency considerations, adaptability and monitoring of projects with agile approaches, continuous value generation, and alignment with the strategic planning of organizations.

According to Bisconti, Orsitto, Fedorczyk (2022), team integration, the promotion of clear communication, and continuous collaboration proactively are essential for the success of complex AI projects, facilitating transparency and traceability of decisions throughout the project and a multidisciplinary approach, which is essential in AI projects.

A methodology for artificial intelligence projects is needed that is comprehensive and flexible considering the entire end-to-end development life cycle. An approach that applies the best practices of project management, with flows and processes oriented to:

- the clear understanding of the problem to be solved;
- the analysis and definition of the most effective solution to solve this problem;
- the development and generation of value in the most efficient way, providing for the correct collection, treatment and preparation of data; the use of appropriate tools; simulations, prototyping; and validation of results;
- the efficient and effective monitoring and control of resources and activities during the project;

- an appropriate approach to the ethical, transparency and privacy issues surrounding data processing.

This proposal proposes to create and make available a new methodological structure for projects for the development of artificial intelligence systems that will fill gaps in current methodologies.

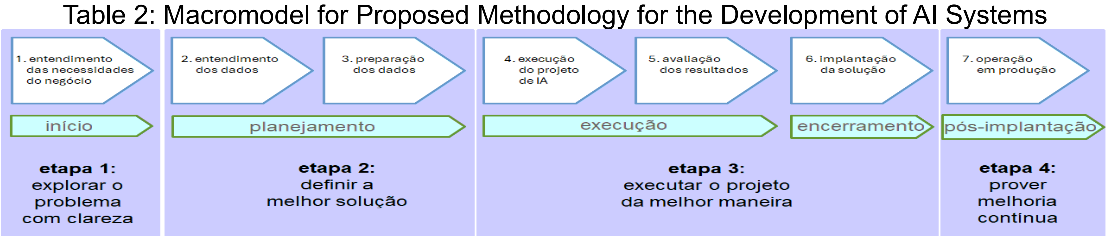
Thus, the methodology for developing AI projects must meet current and future needs, be a reference that allows and facilitates the participation of all stakeholders in the projects, promoting collaboration between different disciplinary areas, with a focus on generating value for the business.

Thus, Chart 2 proposes a macro model of the methodology foreseeing seven phases, seeking to cover the aspects discussed.

It seeks to follow project management recommendations, according to institutes and best practice guides, throughout the development cycle.

The recommended steps for success in adaptive projects and recurring iteration flows are also found as a foundation in the lower layer of representation in Exhibit 2, reinforcing the principles that should always be taken into account in projects of this nature.

Table 2: Macromodel for Proposed Methodology for the Development of AI Systems



Source: the authors

The creation of a methodology implies a systematic and integrated approach that uses standardized processes to support all the activities of the development project (Kerzner, 2001).

The Project Management Institute (2021), when updating its guide with the best practices in project management, in its seventh edition, presented a completely different structure from the one that had been adopted in the previous six guides over the last 30 years, where processes and areas of knowledge prevailed. In this new guide, updated for emerging challenges, management principles and performance domains are highlighted, where continuous value generation is encouraged throughout the project cycle, in an adaptive way according to changes in business needs. The management itself can be

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automated in a few steps with the use of tools made available by PMI® on its Infinity platform, which use artificial intelligence to produce project management artifacts and support decision-making.

The proposal for a comprehensive and flexible methodology that will be developed should be tested with qualitative and quantitative criteria through performance indicators applied in the validation stage of the results of the research project.

Initially, the myriad of possibilities offered by AI requires challenges for organizations such as adapting strategically to obtain a degree of competitiveness and creating objectives that can be achieved by the AI system. In this way, it will result in a relationship of different projects and assignments with varying levels of risk and requirements (Morgan, 2002).

Data is the first important factor, as it is the heartbeat and heart of any machine learning system. Where, the strategic issues that are important to keep in mind when selecting data sources along with associated legal issues, and options related to secure storage.

Second, due to the shortage of AI talent, important challenges and related options for composing an AI team are equally important. In addition, the interdisciplinarity of AI projects, the positioning of the team in the organization, and the organization's strategic expectation of the expected results. Thinking about how to better integrate the AI team into the organization is key to avoiding delays. The decision-making power of managers and teams will need to be considered, that is, if there are departments that need to be involved in decision-making, they should be included in the team.

Another element to consider is Key Performance Indicators to measure how the organization is achieving its objectives, more specifically in this case, the objectives influenced by the AI project.

It becomes important to point out AI projects can not only affect financial results, but can also result in the creation of value for the customer.

This methodology should be presented in the form of a framework, with defined processes and practices, in order to facilitate its application through standards and clear visualization, constituting a consistent basis for its use and dissemination.

Benefits are expected in the efficiency and effectiveness in the development of artificial intelligence system projects, compliance with ethical, transparency, and privacy issues, in addition to alignment with strategic business demands, adaptability and

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collaboration of stakeholders throughout the development cycle, and the generation of value for the end user.

FINAL CONSIDERATIONS

The applicability of this methodological framework must also provide for aspects of quality management, risk management, and change management, to ensure customer satisfaction and better experience.

Validating or refuting these hypotheses will contribute to the body of knowledge on the interplay between AI technology and organizational culture, offering practical insights to other organizations in similar contexts. This study seeks not only to clarify the conditions under which AI can be most effectively implemented, but also focuses on exploring how organizations can strategically cultivate cultures that maximize the benefits of technological innovations.

This research project will contribute, in this way, to the advancement of knowledge in the areas of development of artificial intelligence systems and, in project management, providing benefits not only in the academic field, but also in organizations from all sectors of the economy, with the application of the proposed integrated methodology to improve results in artificial intelligence projects.

As a result of these advantages, you want to solve many problems faster by integrating the models throughout the *design*, construction, operation, and management processes throughout the project lifecycle. A possible contribution to the increase of productivity and efficiency was also observed, especially in the management of information and in organizational decision-making.

As seen in document-based citation analysis, independent examination of research fields makes it difficult to examine studies with a holistic view. In addition to being a new and hot topic, the complexity of the wide range of research areas and the scarcity of studies in the area can create difficulties.

However, in the future, the use of technological platforms for the integration of AI projects can ensure that interoperable information management systems used for different areas of expertise and benefiting from the study of different perspectives can produce efficiency.

Although this study has a great contribution to discover the trend of research from different perspectives, it has limitations such as the period of data acquisition that causes a

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static output, the need for additional analyses, the expansion of coverage in other publications, among others. The findings of this survey provide a broad understanding of the current research approach, research gaps, and future trends in the field of AI research.

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