CMMI & Lean-Based Metrics Governance Model to Ensure Data Accuracy & Consistency for Ai/Ml Applications for Sustainable Operations in Mining Industry

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Abstract: In today's competitive business environment, even small improvements in productivity and efficiency can have a huge impact on company's profitability. Whether it is through reduced lead time/waste, minimized downtime or improved quality, operation managers are looking for any advantage at every stage. Lean management is a long-term operational discipline that methodically seeks to enhance efficiency and quality by eliminating wastage. The concept is being used in varied industries and helped by improved productivity, safety & better management. Lean in being used by few mining companies also at a small scale, which has helped them in limited way.

AI/ML is another important technology used by many organizations. Many global mining companies have also used it for improving operational efficiency, which have helped miners in a limited ways in improving the productivity and safety. Mining companies have to deal with tons of data set generated from heavy machinery and plants, which have to be stored, processed, and stored. There are many challenges in the data set generated/used by AI/ML-application for mining operations.

One of the key challenges in AI/ML is accessibility and availability of accurate & consistent data. To ensure consistency of data there is a need for a governance structure which will guarantee the availability of required accurate data set for AI/ML system.

One possible solution could be, CMMI's metrics processes used by IT companies and have helped in improving quality. CMMI's Metrics related processes are being used extensively by the organizations for better monitoring & control of key measures.

This paper explores the possibility of usage of CMMI's metrics practices with lean implementation in mining for ensuring availability of accurate data sets for AI/ML applications. The proposed framework will put a governance model in place to ensure accuracy & consistency of data to be used for AI/ML-applications in Mining.

Keywords: Lean, Mining, CMMI, Metrics, Ai/Ml.

1. INTRODUCTION

India ranks in the top 10 producers of several minerals worldwide. In the mining sector, it has tremendous promise. More than 90 different types of minerals are produced in the nation, including atomic, non-atomic, metallic, fuel, and minor minerals. The mining industry is crucial to the growth and economics of the country. (Hazra K Arnab, 2013).

From the standpoint of systematic planning, sustainability, and business processes, the Indian mining industry is characterized by a very low level of maturity and a limited adoption of conventional quality frameworks. In an industry that is dealing with issues like cyclical pricing, declining profitability, and shifting demand, running a successful and efficient firm is essential to the long-term viability of the enterprise. (De Coster & Bateman, 2012).

The industry should investigate growth prospects through innovation, cutting-edge technology, and process improvement frameworks for increased productivity, safety, and sustainability in the current competitive and unstable environment. The mining sector in India is highly capital-intensive and has to focus on reducing the waste of important resources, which may be better handled with the help of lean frameworks and AI/ML. Numerous organizations have benefited greatly from lean and AI/ML in terms of bettering the use of machinery, labor, and other resources. CMMI is another process framework used by IT companies across the globe and have helped in improving quality, delivery & customer satisfaction (Keshta, 2022). CMMI's Metrics related processes / practices are being used extensively by the organizations for data governance of key metrics/measures. A combined lean & CMMI's data governance framework for AI/ML application could be of great help to mining industry to ensure availability of accurate, unbiased and consistent data sets.

Data accuracy has proven to be a significant difficulty, according to research, and this industry lacks conceptual and cogent governance structures to guarantee data accuracy. It requires novel frameworks and mechanisms. Therefore, it is necessary to promote lean and other frameworks that would improve the outcomes of mining operations that are sustainable. The paper suggests the usage of CMMI's metrics practices with lean implementation in mining for monitoring & tracking of data/metric across the organization (Harkawat, 2022).

2. LITERATURE REVIEW

2.1. Challenges of Mining Industry
The days of miners just exploring for minerals are long gone. In the future, people that mine for innovation will also be successful miners. In order to maximize their financial and human resources, companies that mine for innovation must create new goods and procedures in-house. If obtaining new systems and resources from outside their company offers them a more viable course of action, they should also think about doing so. In the upcoming years,

both forms of "innovation mining" will simultaneously call for new procedures and guidelines to run the company. (ABB Research, 2020; Deloitte Research, 2020).

Mining and metals executives' top priorities in 2023 will be a more unstable geopolitical landscape, rising demands on sustainability, climate change, and operating licenses. Companies will be forced to look for ways to rethink business models and spur innovation as a result of the additional strain that global disruption will have on expenses, productivity, and labor. How can mining and metals firms go forward with their transformation into purpose-led, low-carbon, digitally enabled organizations while navigating current obstacles like supply chain disruption and growing costs? The mining and metals industry is reacting with more fundamental changes to business and operating structures as 2023 approaches. Miners can reposition themselves for a changing future with new business models, as many organizations are evaluating the advantages of growth, transformation, and rationalization methods. (Deloitte Research, 2020).

One very important and suitable tool for transformation in mining companies can be AI/ML along with Lean and selected processes of CMMI. Lean has been implemented by mining and allied industries and given good benefits to the select organization. It can help mining companies also to ensure sustainable operations. CMMI is being implemented by many IT organizations across the world. The combination of AI/ML, Lean & CMMI's Measurement Processes, as an integrated & structured data governance framework can be attempted for mining industries.

2.2. Lean, CMMI, Ai/Ml and its Usage in Mining Industry

In the current competitive global economic environment in which business is operating in, key resources and the way they are managed are becoming increasingly important. Lean thinking aims to remove wastes from work processes. Developing waste-reducing procedures is the aim of lean management in order to establish a sustainable and productive workplace for both clients and staff. The main goals of lean are to improve workflow, get more value out of what businesses do, and get rid of unnecessary or inefficient tasks (Melton, 2005). Over the years, lean has expanded to many other fundamental engineering areas, such as mining, oil and gas, construction, heavy engineering, etc., due to its success in manufacturing.

Lean was first used and applied in the mining sector a few years ago. It has helped the mining industry throughout the years by lowering costs, improving production and quality, and enhancing safety. The lean framework, which is based on company context, needs, and the internal and external environment, has been used by the mining and metal industries. It is assisting firms in attaining some advantages, but more can be accomplished by striving for additional advancements to satisfy the constantly evolving demands of enterprises and organizations. (Trudel, 2020; Tupa, 2013).

The mining industry faces numerous obstacles while implementing lean, which must be overcome for the industry's sake. Lean implementation is more difficult in mines than in

other industrial facilities since some aspects cannot be controlled, unlike in regulated plants where it is easier to implement techniques like 5S and visual workplace to increase cleanliness and organization. However, operational excellence is achievable, but it necessitates plans for the successful execution and long-term viability of lean projects. (George Alukal & Anthony Manos, 2006; Shah & Ward, 2007).

Artificial intelligence (AI) and machine learning (ML), technologies transforming several segments, including mining. Many organizations have been implementing/developing AI/ML applications in mining. It has been helping to manage assets and resources in most optimal way. However, there are challenges in getting accurate & consistent data for AI/ML applications.

AI/ML is in use in mining industry & operations. Integrating AI, machine learning, and lean into mining operations extends transformative capability, but this integration comes with many challenges and concerns. There are many challenges wrt data availability, accuracy, consistency. In mining, AI application needs a constant stream of high-quality data for decision making in real-time and quickly.

In mining some of the most important issue is data accuracy, incorrect labeling, Duplicity and Biasness etc. Mining operations generate vast amounts of data, and the processing and analyzing of this information require an accurate, safe and strong data-handling procedures. It's equally important to ensure the consistency and correctness of models that make sense of this data, emphasizing the need for routine validation against real-world results through an innovative framework (Sianes et al., 2022).

One of the ways to improve accuracy of data could be, adding best practices of other frameworks like CMMI, which has combination of best of the processes used in IT companies. Organizations can use it for ensuring proper data governance and provide required accurate data feed to AI/ML applications (Vinuesa et al., 2020).

In parallel, there is also an urgent necessity to having a culture of maintaining, refining, and using the data by practitioners, SMEs & Management. Also, the successful adoption of AI centers around a strong mapping of metrics with business objectives that can effectively connect with org vision & mission.

A strong Data governance is essential for preserving, guaranteeing, and improving data quality in organisations. It includes all of the procedures, rules, guidelines, and technological advancements that control the accessibility, usability, security, and integrity of data. Better decision-making, operational optimisation, regulatory compliance, and competitive advantage are all benefits of effective data governance for organisations. Addressing the problems with data quality in AI requires the implementation of a thorough data governance structure. Data stewardship, data quality management, data privacy and security, and data architecture are just a few of the components that make up data governance.

Understanding the organization's objectives, data quality criteria, and current data management procedures is essential to implementing an effective data governance structure.

Organisations must define measures for data quality, set goals for data quality, and frequently assess data quality performance. In order to assist the data governance process, organisations need also invest in data governance technology including data catalogues, data lineage tools, and data quality management systems. Organisations can greatly enhance data quality and unleash the full potential of AI by implementing a strong data governance structure. Furthermore, establishing a data-driven culture inside an organisation depends on good data governance. Data governance aids in the dismantling of data silos and the sharing of data assets by encouraging collaboration and communication across various departments and stakeholders. This makes it possible for businesses to make better use of their data and get insightful information for making strategic decisions (Guba Yvonn As, 1994; Hou et al., 2021).

Education and training are essential elements of data governance. Making sure staff members are well-versed in data quality principles, resources, and best practices fosters a common goal and dedication to preserving high-quality data. More dependable and accurate AI models that spur innovation and provide businesses a competitive edge may result from this. Additionally, a structured framework facilitates the adoption of new technologies, procedures, and systems as well as the transformation of culture. Promoting an organizational culture that welcomes technological innovation can assist the company in taking the right course. (Bobrikov et al., 2019; Yang et al., 2022).

2.3 CMMI and Measurement Analysis (Ma) Process Area

The first multi-domain maturity framework was created in 1986 by Carnegie Mellon University's Software Engineering Institute (SEI). The first maturity model to direct software development was the Capability and Maturity Model (CMM). CMM the Capability Maturity Model Integration (CMMI) was first published in 1993. The CMM was created especially to offer a structured, disciplined framework for addressing issues related to software management and engineering processes. Later, CMM evolved into the Capability Maturity Model Integration (CMMI), which offers a means of evaluating and showcasing an organization's practices and operations in relation to recognized standards.

An outcome-based performance improvement strategy that has been shown to produce quicker, better, and less expensive results is CMMI Performance Solutions. The well recognized standard that raises organizational performance and capacity is called CMMI. Building and implementing new capabilities that produce consistently measured outputs and outcomes is made easier with the help of CMMI. For more than 25 years, ISACA®'s Capability Maturity Model Integration (CMMI®) model has helped high-performing companies achieve measurable, long-lasting business outcomes. The CMMI model was initially developed for the U.S. Department of Defense to evaluate the quality and capability of their software contractors. Since then, it has been extended beyond software engineering to assist organizations worldwide, across all industries, in comprehending their present performance and capability levels and providing guidance to maximize business outcomes. Businesses in 106 countries employ the model. With the aid of CMMI Performance Solutions, companies may rapidly assess their present performance and capacity level in

relation to their own business goals and to those of other organizations of a similar nature. Thousands of internationally renowned businesses, including numerous Fortune 500 companies, have benefited from CMMI's performance improvement paradigm. (Product Team, 2010).

CMMI's Measurement and Analysis (MA), can help mining organizations to develop and sustain a measurement capability used to support AI/ML applications and management information needs. It involves the following activities:

- Specifying objectives of data/measurement and analysis so that they are aligned with identified information needs and project, organizational, or business objectives and new applications.
- Specifying data/measures, analysis techniques, and mechanisms for data collection, data storage, reporting, and feedback
- Implementing the analysis techniques and mechanisms for data collection, data reporting, and feedback
- Providing objective results for better results of AI/ML applications.

CMMI's Measurement and Analysis (MA), with some customization can be used data governance which can feed accurate data of AI/ML applications.

2.3 Research Gap
There are many companies implementing lean and AI/ML to improve organizational efficiency and effectiveness. AI/ML requires a systematic metrics / measurement-based system for accurate prediction and decision making. So, there is need to define a structured measurement framework for better decision making through AI/ML in mining organizations.
In order to guarantee that their AI systems generate precise, trustworthy, and objective findings, organizations and researchers engaged in the creation and use of AI mining should give priority to addressing data quality issues. Define and understand the key aspects of data quality and how they affect AI systems to achieve this. In order to maintain and improve data quality, we propose a robust data governance framework, emphasizing the need for companies to invest in robust data governance processes and technologies.
As per author's best of knowledge, there is no measurement framework for AI/ML application which is based on CMMI's measurement & analysis process area and ensure data accuracy and consistency (Card, n.d.).

3. METHODOLOGY

The researcher decided to use the secondary data that was available from the various businesses in order to construct the new framework. The researcher looked at how firms used the frameworks and processes that were already in place. Many organizations utilize CMMI V1.3 (Fang et al., 2012; Liberato et al., 2015).
The researcher made the decision to develop a new framework using the practices and sub-practices of the measurement & analysis process area. After studying every measurement and analysis process area, a new Framework for mining organizations was suggested.

New Framework Combining Measurement Analysis (Ma) Process Area (Pa) and Lean Practices for Ai/Ml-Application's Data Governance

Data governance throughout all the organization can be done through a structured measurement program using CMMI processes. The AI/ML-application and management-driven metrics program can be defined using CMMI's MA PA which is proven and resulted into a consistent result for many organizations.

Following table shows CMMI's Measurement & Analysis (MA) Process Area's (PA) Practices (as defined in CMMI-Dev V1.3 Model) and proposed Measurement Practices which can be used to design a Metrics Program to ensure better AI/ML-data governance in the organization –

CMMI MA PA's Specific Practices (SP)	Proposed AI/ML Data Measurement & Governance (AMDMG) Practices <SP Number e.g. AMDMG SP > <Practices> <Process>
MA.SP 1.1	AMDMG SP 1.1: Establish AI/ML Metrics Objectives
	Establish and maintain AI/ML measurement objectives derived from identified information needs and objectives of the organization & management implementing AI/ML
MA.SP 1.2	AMDMG SP 1.2: Decide Data / Metrics to be made available for Lean & AI/ML applications
	Specify metrics to address AI/ML-based applications measurement objectives
MA.SP 1.3	AMDMG SP 1.3: Define AI/ML Data Gathering & Storing Mechanism
	Specify how AI/ML measurement data are acquired and put in storage.
MA.SP 1.4	AMDMG SP 1.4: Define AI/ML Metrics Analysis Procedure
	Specify how A/ML measurement data are analyzed, reported and communicated
MA.SP 2.1	AMDMG SP 2.1: Get the required AI/ML Metrics Data
	Get specified AI/ML metrics data.
MA.SP 2.2	AMDMG SP 2.2: Conduct Metrics Analysis and Model Validation
	Analyze and infer the metrics data and AI/ML Models
MA.SP 2.3	AMDMG SP 2.3: Store up Data, Models, Results and Findings
	Manage and store measurement data, AI/ML-models, specifications, findings and analysis results
MA.SP 2.4	AMDMG SP 2.4: Share / Feed Metrics Analysis and AI/ML modelling Results
	Communicate results of Metrics, AI/ML modelling and analysis

Table 1: Mapping of CMMI Measurement & Analysis (M&A) Process Areas (PA) and Proposed AI/ML Data Measurement & Governance (AMDMG) Processes (Source: Self Research and Learnings)
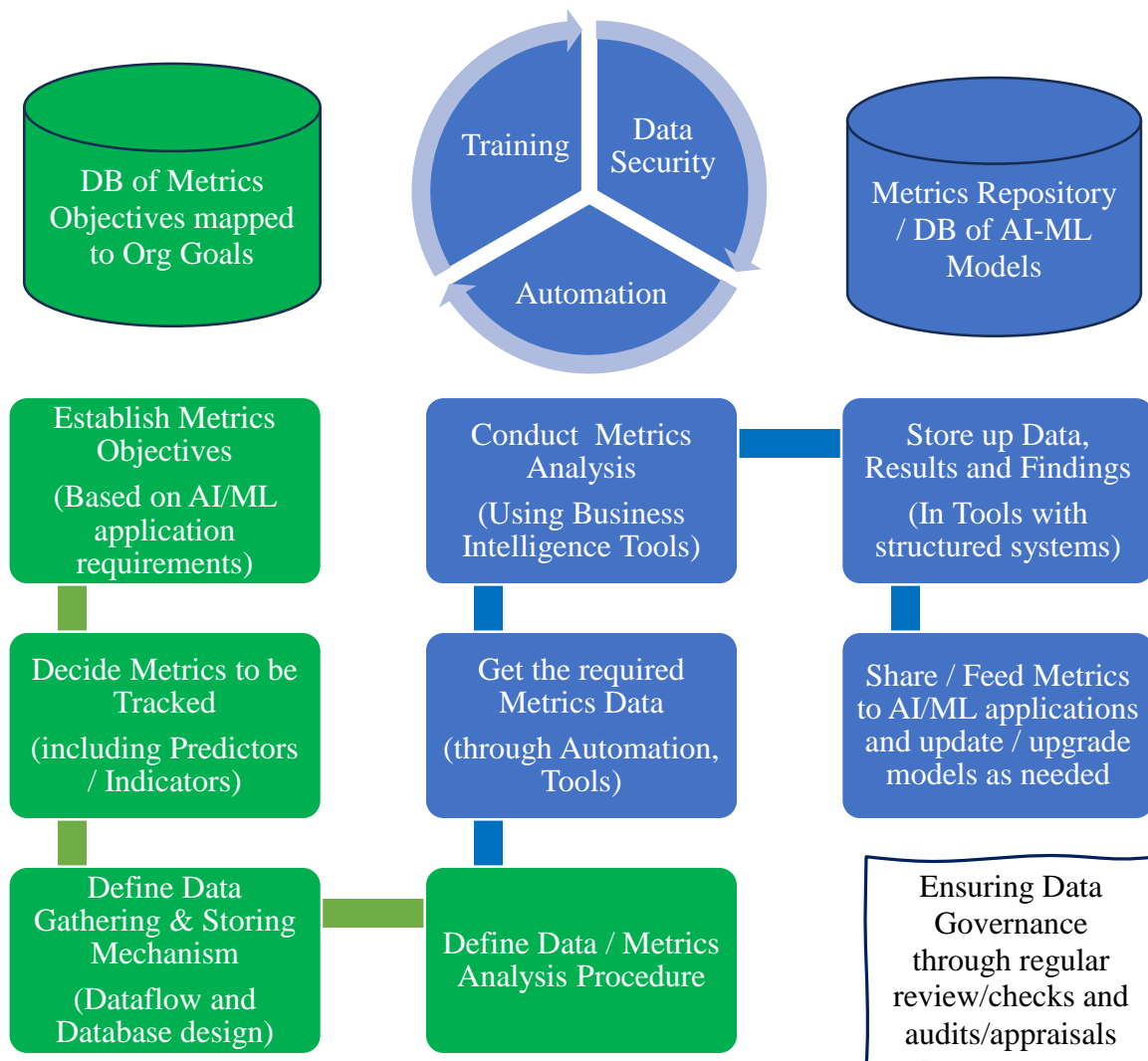
Figure 1: CMMI's M&A-based Measurement Framework for Data Governance of AI/ML applications in Mining (Source: Self Research and Learnings)

Mining companies can use this proposed framework with more customizations as per organizational needs and ensure more rigours monitoring of quality of data used/available for AI/ML applications.

Lean metrics framework can be used to support CMMI and AI/ML framework. The key metrics data related to lean performance could be MTBF, MTTR, % Rework, % improvement in mining operation's cycle time, % increase in productivity etc. It's an indicative list and more can be added as needed.

The new proposed framework can address the complexity of most mining operations, as well as their sheer magnitude, safety-critical emphasis, geographic isolation, environmental effect, and other issues. Benefits and a favorable business impact are possible with this coupled

structure. Businesses who are adept at applying these best practices across the board will have an advantage when it comes to utilizing AI/ML solutions. Businesses will be able to increase efficiency, guarantee sustainable operations, enhance health and safety, and make more accurate judgments.

Following Points Need to be Considered for Better Regulation of Data and Governance:

- Quality standards and policies for data must be defined and put into action.
- Throughout the lifecycle of the data, it is important to keep a close eye on their quality and maintain control. Quality data and holding ourselves accountable should be part of a culture we strive to create. The sharing, integration, and management of data can be enhanced through various means. The optimization of data management techniques should be prioritized.
- Improved data sharing is crucial for seamless exchanges between different systems. The integration of various data types can be achieved using appropriate methods. Regulations and laws must be followed carefully to maintain compliance.

In the study, researchers have emphasized the need for quality data frameworks and policies to be created and put into place. They have also demonstrated that AI/ML systems may provide reliable data quality if organizations follow certain best practices and methodologies. The structures and processes for data governance must be put in place to ensure appropriate management. Governance data architecture and procedures make data management accountable and responsible. Establishing governance structures and procedures is necessary to guarantee the proper usage of data. To properly handle data, those responsible for handling it must have clear policies and processes in place. Proper governance ensures proper data management and the granting of rights, permissions, and access. Data can be lost or misused in the absence of these systems and procedures, which affects an organization's overall performance.

Additional Measures to Ensure Best Practice & Data Quality:

To guarantee data quality, regular evaluations and audits must be performed. Don't forget to perform these tests irregularly. It is recommended to apply enrichment techniques along with data cleansing and validation. Data lineages and traceability solutions are tools for enacting change. Adoption of machine learning- and AI-based solutions is strongly encouraged since they provide potent tools for enhancing data quality. Employee training sessions should cover the best data quality procedures. Alliances between coworkers and associates can be created to improve the data's quality. By implementing these best practices, businesses may enhance the performance and dependability of their AI systems, which will raise the caliber of the data used.

To fully utilize AI and improve results, it is essential to implement data governance and best practices across a variety of dimensions. Our analysis shows that to enable the successful development and implementation of AI systems, organisations must solve data-quality issues. Data quality is important and should be given high emphasis by businesses using AI.

4. RESULTS AND DISCUSSIONS

This study provides a comprehensive analysis of the challenges related to data quality for artificial intelligence, emphasizing how important it is to understand and address data quality issues in the design and development of AI systems.

In order to guarantee the availability of accurate data sets for AI/ML applications, this study investigated the feasibility of using CMMI's metrics standards with lean implementation in mining. A governance model is being proposed to guarantee data consistency and accuracy for usage in mining AI/ML applications. Mining companies can use this proposed framework with more customizations as per organizational needs and ensure more rigours monitoring of quality of data used/available for AI/ML applications.

Limitations

The thorough examination of the difficulties associated with data quality for artificial intelligence described in this paper highlights the significance of comprehending and resolving data quality concerns in the design and implementation of AI systems. Although the proposed framework will work as a useful manual for businesses looking to improve their data quality management initiatives and raise the efficiency and dependability of AI systems. It has few limitations.

The proposed framework is based on the available literature and built based on CMMI & lean implementation experience of the author. The framework needs to be validated by mining companies and lean practitioners.

5. CONCLUSION AND WAY FORWARD

Lean can be implemented in more structured way in mining by combining the available best practices & lesson learned from other industries. A structured implementation of Lean & CMMI PA in mining can provide a clear direction for applications in various key operations specifically in operations. If implemented with proper planning & with key selected CMMI processes, It will help in reduction of wastage of key resources and improve the productivity, safety, machine's availability and will result into more sustainable mining.

Implementation & Validation of this framework, followed by any adjustments would greatly benefit both further research and its practice in the mining sector. In future the framework can be enhanced by adding more best practices of other improvement frameworks like BSC, CMMI (Monitoring & Tracking Processes), six sigma, value engineering etc.

Although this research has offered a thorough review of the difficulties with data quality for AI, it had a number of drawbacks. First, the dimensions of data quality, data governance, and best practises were the primary focus of our investigation. The performance of AI and the quality of the data may also be influenced by other variables, like organisational culture and technical infrastructure. Second, even though we consulted a wide range of literature sources, this analysis may have overlooked some important publications. Final point: Future empirical research is required to further validate and broaden our findings, which were mostly based on a synthesis of the research in the new & innovative area.

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