International Journal of Accounting and Economics Studies, 12 (3) (2025) 180-186

SPC

International Journal of Accounting and Economics Studies

Website: www.sciencepubco.com/index.php/IJAES
https://doi.org/10.14419/s0n2f394
Research paper

Enablers to The Adoption of AI/ML Technologies in Process Industries

Sudhir Sohoni [1] *, Prafulla Pawar [2], Umesh Raut [3]

[1] *Research Scholar, Savitribai Phule Pune University, Pune, Maharashtra, India*
[2] *Senior Professor, Savitribai Phule Pune University, Pune, Maharashtra, India*
[3] *Associate Professor, Savitribai Phule Pune University, Sub Centre Nashik, Maharashtra, India*
**Corresponding author E-mail: sohonisudhir@gmail.com*

Received: June 13, 2025, Accepted: July 15, 2025, Published: July 21, 2025

Abstract

The process industry, from its inception, is data intensive, and the advent of information technologies (IT) has rapidly digitalized. Mathematical modeling for a purpose has been the axiom. This is a qualitative study in four large entities in the oil and gas sector and in the automotive sector. The grounded theory method (GTM) has been used by the authors for data collection and its subsequent analysis. This has enabled a comprehensive insight into understanding the factors that influence the adoption of AI / ML technologies. The key themes that emerge are, in the creation of technological readiness include data infrastructure, advanced analytical capabilities, the use of tools such as cloud computing, and the democratization of data. Leadership drive is a critical success factor to facilitate change management, allocation of resources, and constant reviews to resolve issues. The findings provide practical guidance for the adoption of AI/ML technologies in the process industry.

Keywords: *Artificial Intelligence; Focus Group Discussion; Grounded Theory Method; Process Industry; Technology.*

1. Introduction

The process industry has been data-intensive since its inception. With the availability of computing power, data storage facilities, internet connectivity, devices for collecting real-time data, and the refinement of existing algorithms, the industry is poised to surpass any other in the rapid, extensive, and widespread adoption of AI/ML technologies [1]. Such adoption will significantly contribute to gaining a sustainable competitive advantage and improving operational efficiency and decision-making [2 - 4]. The study focuses on the enablers of AI/ML adoption and how organisations can integrate these technologies into their daily operations. While there are some notable barriers to adopting AI/ML technologies, addressing them is beyond the scope of this study. The characteristics of the process industry include continuous operations, either in batch production or with continuous output, which have distinct features. The process is irreversible, with raw materials often being gases, chemicals, slurry, minerals, and fossil oil. The nature and attributes of the input raw materials can vary greatly. The variability of the output should be nearly zero, regardless of the raw material characteristics. The process produces an entirely new product, and the organisation typically owns the materials [5]. Most of the high technology used in the process industry is proprietary, making it challenging to incorporate digital technologies [6]. Opportunities for process optimisation—based on market needs, efficiency improvements, and predicting maintenance requirements, including replacement of plant and equipment—can be realised through adopting AI/ML technologies [7]. Implementing AI/ML requires a shift in the mindset of ground-level engineers, along with sufficient data literacy [8], [9]. The TOE Framework, combined with the DOI Theory [10], [11], provides comprehensive insights into the adoption process. Aligning broader organisational goals, developing a strong data framework, and fostering a culture of learning are essential for the successful adoption of AI/ML technologies in the process industries. According to the World Economic Forum's 2011 [12] report, the process industry does not fully utilise data due to barriers such as integration issues with legacy systems and the reluctance of original equipment manufacturers (OEMs) to share technologies unless organisations use only those developed by the OEMs.

The current research is an empirical study that includes four semi-structured interviews with members of the leadership team who decided to adopt AI/ML technologies and two focus group discussions (FGD) in which a total of eighteen employees participated, representing data scientists, data engineers, platform specialists, ICT professionals, operations staff, and end users. Hence, the data is from knowledgeable and technological experts who created the use cases and subsequent AI/ML applications, more than 150 of them as of the date of the interaction. This method is considered the most reliable and trustworthy means of gaining insights into real-life issues and the execution of intent to adopt AI/ML technologies [13 - 15].

The study provides practical guidance to process industry functionaries on how to leverage the enablers already existing in every organisation and swiftly adopt AI/ML technologies to gain a sustainable competitive advantage. The study also contributes to the emerging body of knowledge on the adoption of AI/ML technologies, particularly in the process industry.

2. Literature review

The state of technological readiness is a crucial factor for the adoption of innovation, especially in the context of AI/ML adoption. The process industry is complex as it generates millions of data points each minute, requiring extensive data capture, storage, and processing infrastructure. This is where data lakes and cloud computing become significant enablers, offering scalable and cost-effective solutions [16], [17]. The TOE Framework by Tornatzky and Fleischer (1990) [10] and the DOI Theory by Rogers (2003) [11], when considered together, explain how innovations can be adopted at both the organisational and individual employee levels. Technological, organisational, and environmental contexts influence decisions at the organisational level, while DOI focuses on the internal ecosystem of an organisation in adopting innovations. According to Rogers (2003) [11], five factors influence the adoption of new technologies: "relative advantage, compatibility, complexity, trialability, and observability." Both the TOE and DOI frameworks are valuable for understanding the enablers of AI/ML technology adoption. There is extensive literature on innovation adoption within the process industry, offering insights into improving operational efficiency, safety, and process optimisation [18]. All these benefits can be effectively harnessed by integrating AI/ML technologies through building technological readiness, organisational commitment, and managing environmental factors [19], [20]. Adoption of AI/ML technologies helps reduce variability in processes and systems, increase output, improve product quality, provide real-time feedback on plant and equipment performance, and support prescriptive maintenance and process optimisation. Building a resilient technological and data infrastructure, integrating advanced analytical capabilities, and scaling computational resources are crucial for successful AI/ML integration [16], [21]. One of the pioneering innovations has been the availability of cloud services not just for storage but also for computing and hosting AI/ML applications that can be customised, offering flexibility and the ability to meet organisations' specific needs—especially in makin, data accessible on a need-to-know basis for decision-makers [22], [23]. Ensuring the integrity of the data framework—in terms of accuracy, consistency, and correctness—is crucial for the deployment of AI/ML models and must be maintained through technical expertise [24].

Moreover, the development of user-friendly AI/ML tools and platforms has facilitated the democratisation of these technologies, enabling non-experts to leverage advanced analytics for decision-making [22]. The integration of AI/ML technologies with existing enterprise systems, such as Enterprise Resource Planning (ERP) and Manufacturing Execution Systems (MES), further enhances their utility and adoption [25]. The leadership commitment, nurturing a culture of innovation and creativity, eradicating the fear of failure, and alignment with the organisation's strategic goals are the enablers for managing change, collaboration, and teamwork within and across departments [26]. According to Fitzgerald et al. (2013) [27], the ability of an organisation to prioritise the trajectory of digital transformation, provide resources as needed, and continuously review progress on implementation are the cornerstones for successful AI/ML implementation. Demonstrating that AI/ML leads to skill upgradation and a new way of working, thereby alleviating fears of job losses, enables the reinforcement of confidence and wholehearted support from employees to adopt new technologies [28]. Continuous, transparent, and credible communication, along with clarity on expectations, apart from the organisational and personal benefits of adopting AI/ML technologies, acts as an enabler [26].

A thorough understanding of the external environment, which is dynamic and complex due to multiple factors such as geopolitics, market trends, changes in customer preferences, competition, and comprehension of regulatory guidelines, acts as a key facilitator for the adoption of AI/ML technologies, as all these elements contribute to enhancing the organisation's competitiveness [29], [30]. Proprietary technologies employed by OEM suppliers, operating within departmental units with varying data presentation formats, require addressing through education, technology, and awareness to enable the full integration of AI/ML into existing legacy systems [12]. Effective utilisation of current systems, such as ERP (Enterprise Resource Planning) and MES (Manufacturing Enterprise System), is vital for supporting the implementation of AI/ML technologies within the process industry [25]. Organisations with a prior history of success in adopting innovation and those proficient in managing change—utilising clear, concise, continuous, comprehensive, and consistent communication, employee engagement, and well-defined requirements—have maintained an advantage in assimilating new technologies more swiftly, with fewer iterations [26]. The most influential enabler centres on continuous learning, skills development, and providing opportunities to apply these skills and knowledge, [24], [31]. Numerous empirical studies on the adoption of AI/ML in the process industry are available in the literature. For instance, McKinsey & Company (2025) [32] reported significant savings achieved through enhanced operational efficiencies, reduced variability in processes and systems, predictive maintenance, and notable improvements in product quality. Organisational culture and goal alignment are essential enablers. To conclude, the observed research gap is the relationship between the adoption of AI/ML technologies and an organisation's competitiveness. Additionally, an empirical study could be conducted to investigate the relationship between leadership style and the speed of AI/ML technology adoption.

3. Research objectives

- To understand the motivation for the adoption of AI/ML technologies.
- To understand how the organisation leveraged the enablers for the adoption of AI/ML technologies.

4. Research questions

- What outcomes were sought to be achieved by the adoption of AI/ML technologies?
- Specifically, what actions were taken by the organisations to leverage the enablers?

5. Methodology

5.1. Research design

The research design is most appropriate as it allows a deep exploration of individuals' experiences and multiple perspectives, thereby examining a complex phenomenon [33]. The study, employing a qualitative approach—specifically the grounded theory method (GTM)—also aids in understanding the context, including motivations, behaviours, perspectives, and attitudes across various levels within the organization [34]. This is an exploratory study aimed at identifying enablers for the adoption of AI/ML technologies within an organisation, and GTM offers a detailed platform for data collection, especially given the varied and multidimensional nature of evolving technology, which may not be fully captured through quantitative research methods [35], [36]. Primary data sources included semi-structured interviews and FGDs with participants who were deeply involved, committed, and actively driving the adoption process, sharing similar characteristics and experiences [37]. The dynamic exchange of views, diverse opinions, and observations, and building on one another's ideas facilitated the exploration of complex issues [38]. FGDs provided insights into individual and collective experiences, reflecting on the outcomes of specific actions and personal experiences, particularly regarding organisational and environmental factors influencing AI/ML adoption. These provided rich, detailed data that addressed the research questions [39], [40]. The FGDs were particularly useful for identifying common themes and patterns across the four organisations involved in the study, thereby responding to the research questions [41].

5.2. Data collection

The study employs GTM for data collection, conducting semi-structured interviews with leadership team members who decided to adopt AI, as well as FGDs with employees involved in creating use cases and AI/ML applications. These included data scientists, data engineers, technology platform specialists, line managers, supervisors, and IT specialists. Four semi-structured interviews were held, along with two FGDs consisting of 9 and 10 participants, respectively. This approach enabled the collection of insights from leadership, as well as those who implemented AI at the operational level, and users involved in daily activities. The same introductory brief was used in all semi-structured interviews and FGDs to ensure consistency. Purposeful sampling was employed to gain a deep understanding of the adoption decision and the enablers—both existing and newly created—that helped the organisation achieve a competitive edge. The audio transcripts serve as inputs for extracting data. The data was then analysed into themes, constructs, and dimensions for each construct. This is illustrated in Fig. 1.

Purposeful sampling was used to ensure all participants played a significant role in adopting AI/ML technologies and were explicitly exposed to shared experiences [42]. This sampling method allowed the researcher to identify and gather insights that were useful and relevant to the research questions [35]. A total of 23 participants took part in semi-structured interviews and FGDs, representing roles across technology, manufacturing, business management, and data/technology specialists, thereby providing a comprehensive understanding of the factors influencing the adoption of AI/ML technologies.

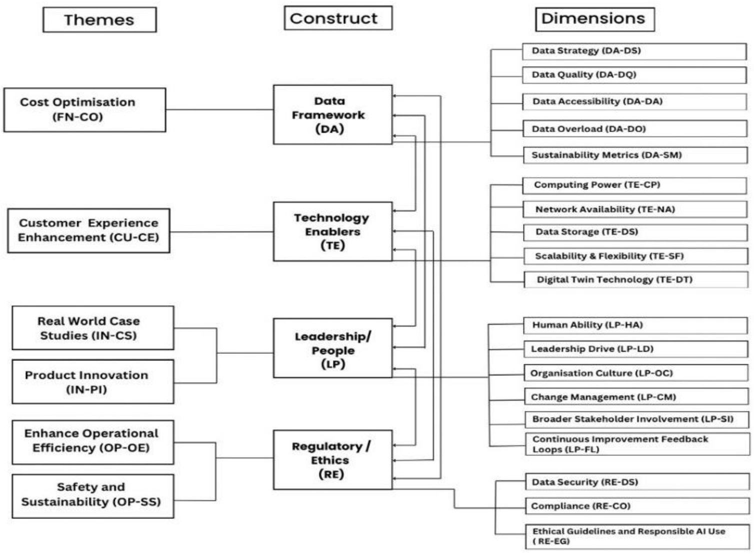

Fig. 1: Themes, Constructs, and Dimensions.

5.3. Data analysis

The transcripts of the semi-structured interviews and FGDs were analysed using thematic analysis, which is a qualitative research method that utilises the extraction of data, analysis, and creation of patterns or themes from the data that emerged [43], [44]. According to Guest et al. (2012) [45], the method of thematic analysis is most appropriate for exploring complex and multidimensional data, as it enables the researcher to capture the varied ideas and diversity of thinking and experiences of the participants. This is illustrated in Fig. 1. Using the process provide by Braun and Clarke (2006) [43] the researcher first got familiarized with the data [46], as for the researcher it was a new subject to study by reading and listening to the audio recordings to comprehend the various perspectives and experiences being expressed by the participants, next was use of open coding in a reiterative manner to align with the research questions [47], from here emerged the themes that represented the various pertinent topics within the scope of the research study [43], namely the enablers to the adoption of AI / ML technologies in process industry. The review of the themes confirmed the consistency and comprehensibility when compared with the coded data sets [35]. The titles of themes emerged automatically based on the transcripts and patterns observed, as applicable to the process industry, since all participants were from this sector. The naming of the themes was based on the emerging outcomes and dimensions that led to their identification [43], [44].

The main themes were technological, organisational, and environmental enablers. Within technological enablers, participants identified robust data infrastructure, the availability of an internet network, computing power—especially on edge devices—to reduce latency in real-time decision-making, advanced analytical capabilities, scalable computing, and expertise in leveraging legacy systems and data as primary enablers for productivity.

5.4. Key observations

The organisational enablers highlighted by the participants were leadership commitment and drive, organisation-wide education and training on digitalisation, a culture of innovation, transparency in communication, and clarity in adopting AI/ML technologies. They stressed making the business the decision-maker and ICT the enabler, emphasising the importance of aligning use cases with the organisation's strategic goals, resource allocation, and addressing concerns about job loss due to AI/ML adoption. Within the environmental domain, market dynamics and the need to maintain market leadership emerged as significant enablers, driving the use of a regulatory framework to develop better and more secure AI/ML applications, with the support of regulatory authorities.

6. Results

Delving deeper into the qualitative data from the transcripts of semi-structured interviews and FGDs uncovers the enablers of AI / ML adoption in the process industry. The findings highlight key themes that offer a thorough insight into what drives the uptake of AI/ML technologies. The analysis identified several significant enabling factors, including robust data management practices, multi-layered collaboration across departments, leadership commitment, access to high computing power, extensive data storage facilities, the ability to integrate legacy systems, employee engagement, and, crucially, the alignment of use cases with the organisation's business needs. This analysis results from a thematic approach conducted within the complex interplay of technological, organisational, and environmental factors affecting AI/ML adoption.

Fig. 2 is the conceptual framework for the adoption of AI in the process industry. In Fig. 2, each of the constructs serves as an enabler for the adoption of AI.

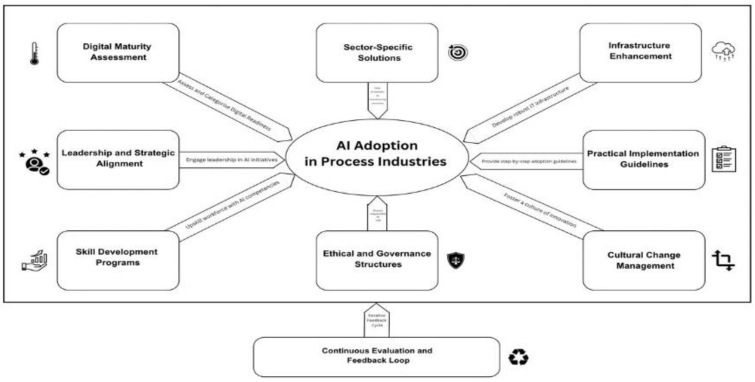

Fig. 2: Conceptual Framework of Enablers to the Adoption of AI in Process Industry.

In the conceptual model shown in Fig. 2, eight constructs serve as enablers. The ongoing evaluation and feedback loop guarantees that the progress of adoption is monitored, and midcourse corrections, if needed, are promptly applied. A description of the eight enabling constructs identified through thematic analysis is outlined as follows:

Sector-specific solutions are essential because, within the process industry, there are numerous different types of sectors, including oil and gas, forgings, foundries, food processing, tyre manufacturing, and others. Each sector has its unique features. Therefore, the strategies and tactics will differ based on the different requirements dictated by each process. Infrastructure enhancement is a key enabler, as nearly all equipment used in the process industry is supplied by original equipment manufacturers (OEMs). Take the oil and gas sector, for example; the use of algorithms has been established for a long time. Now, with improved computing power and internet connectivity, real-time data collection through various devices has become a significant enabler. The same applies to the rest of the process industry.

Practical implementation guidelines emerge as a library of algorithms and AI/ML applications where only the observed metric or reading needs to be inserted, and the solution is ready, thereby saving time on diagnostics. The algorithm determines what requires attention. Cultural change management is a critical enabler to develop trust in data and the output of the algorithm. This is especially so as most of the time, engineers have a thought process about how a machine can think better than a human. However, when millions of data points are generated each minute of operation, human ability has inherent limitations, and this is where high-quality AI/ML training data, often generated by humans, plays a vital role. Second is the aspect relating to collaboration and teamwork in the creation of the data, where a unified vision set out by the leadership team provides traction for effective cross-functional working. Skill development programs are like the glue that binds all with a shared language and understanding of the nuances in AI /ML technologies. Organisations that undertake comprehensive and extensive education and training programs, as seen in the participating organisations, develop capabilities in the workforce related to digital technologies. This acts as an enabler for the adoption of AI/ML technologies.

Leadership and strategic alignment are of paramount importance, as merely undertaking AI/ML adoption as a project does not serve any purpose. The need to dovetail AI strategy with business strategy yields improvements in financial, operational, customer experience, and internal processes, leading to innovation and creativity. Leaders need to drive the process by conducting continuous reviews, allocating resources, resolving issues relating to priorities, and recognising group and collective achievements. Digital maturity assessment is essential to gain an insight into where the organisation stands as of date, what kind of skills are required, what can be developed internally, what needs to be infused, and what can be outsourced. These are all strategic areas that need to be addressed to mitigate any risks arising from and during the adoption of AI/ML technology. A continuous evaluation and feedback loop provides knowledge on what needs to be corrected, where deviations are permissible, how outlier data points are identified, and whether the information is being understood and addressed. The feedback mechanism supports motivation among engineers and technologists who are working on the adoption of AI/ML technologies.

To be ready for the adoption of AI/ML technologies, the organisation(s) embarked on a comprehensive education and training drive on digital technologies, starting at the leadership level and extending to the security staff. This single move not only eradicated any fears of job loss but, on the contrary, enthused employees, as they saw an opportunity to upgrade their skills, make their tasks easier and more accurate to perform, thereby improving both their performance and that of the department they worked in. Furthermore, the use of libraries of algorithms that were developed for problem-solving enabled an increase in productivity [22]. This was truly the democratisation of data in action in real life [16]. The availability of cost-effective data platforms for storage and processing, cloud computing for advanced analytics, the integration of ERP and MES with new technology platforms, and scalable computing resources all enabled the adoption of AI/ML technologies [25]. All the organisations that participated in the research had a clear strategic vision. The leadership drive was evident in terms of granting autonomy to the AI / ML teams and task forces, constant reviews that focused on bottlenecks and interdepartmental issues, breaking down resistance with logic and ratioand nale, being transparent about the future gains likely to accrue by the adoption of the AI / ML technologies were significant tactics. The leadership team demonstrated, through their actions, that failure is not inherently bad if it leads to learning and the avoidance of repeating the same errors. No one was penalised for trying something new and different, and this action encouraged risk-taking, removing the fear of failure and fostering a culture of entrepreneurship. This aligns with what Westerman et al. (2014) [26] highlight, who emphasise the characteristics of leadership in embracing change and driving digital transformation. However, another facet common across all organisations in the study was the transparent and honest cross-functional collaboration across levels that acted as an enabler. The most noteworthy aspect among employees was one relating to the acquisition of new knowledge, its application, and the transfer of this knowledge to others, which had a multiplier effect and continuously created a new platform of knowledge and understanding. The result was the development of skills and an embracing of change rather than resistance to it [28]. The impetus in the environment that enables the adoption of AI/ML technologies is driven by competition, industry structure, consumer preferences, and the government's regulatory framework. The higher the competition, the greater the incentive to adopt AI/ML to maintain or improve market position. This finding is consistent with the study of Porter & Heppelmann (2015) [29]. Regulatory frameworks that promote data sharing and innovation facilitate the adoption of new technologies, particularly AI/ML technologies [30]. Factoring for obsolescence has been performed by organisations in the study, particularly about data security and safety, considering regulatory mechanisms across various countries [29].

Data strategy and data management emerged as one of the most important themes. From the transcripts, it is evident that participants gave the most importance to data integrity, accuracy, consistency, and transparency for any successful AI adoption. Investment in data governance frameworks was accorded utmost importance to ensure the reliability and validity of AI/ML models. The integration of existing ERP and MES platforms with new AI/ML applications greatly improves decision-making and streamlines operations [48]. Organisational culture and management of transformation promote the acceleration of AI/ML technology adoption. Clear communication on expectations from AI / ML adoption by the leadership team, making the business the champion for identification of use cases and adoption process, assuaging any misapprehensions regarding job security, providing opportunities to use the newly acquired skills and demonstrating that the value creation is on a different scscale/levely the use of AI / ML technologies creates a culture where employees embrace rather than resist the changes being made in the way of working [49].

7. Discussion and conclusion

This research study was conducted across four organisations in the oil and gas and pneumatic tire manufacturing sectors, where demonstrable outcomes have been achieved in the areas of yield improvement in petrochemicals, significant improvements in operational efficiencies, enhanced equipment and personnel safety, energy savings, and improvements in all sustainability indices. In today's technology landscape the availability of extensive data storage facilities, cloud computing, competent system integrators (SI), capability of talent to deliver in-house solutions, use of edge devices for real-time data based decisions, internal talent developing physics based applications to minimize variability of material in process at various stages of production, identify precisely what equipment's need to be replaced based on an aging of equipment hence incorporation of metallurgy dimensions as part of the algorithm, and use of domain knowledge is proving to be a critical enabler that goes beyond the AI / ML models [22], [16].

One strategic decision in a participating organisation completely changed the game for adoption, making the business the champion of AI/ML adoption and technology an enabler. Through the conduct of hackathons, FGDs, and customer visits, use cases were identified that provided tangible business outcomes and vastly improved customer experience. This resulted in galvanizing the entire process of adoption with every individual being a touchpoint by way of education, training, in use case generation, applying solutions on shopfloor, providing feedback on what is working and what is not working and thereby creating a robust internal ecosystem and truly democratizing the process of adoption of AI / ML technologies [27], [26]. The intense competition among the organisations participating in this research was a key impetus for the decision to adopt AI/ML technologies [29]. The support from governmental agencies such as the NITI Aayog in India [50], the (NITI Aayog Report, 2018) provided a push for technology adoption. Data safety and security are concerns that are addressed by multilayered technology firewalls, as well as periodic audits by multiple experts in data security and by data security audit firms.

The TOE by Tornatzky and Fleischer (1990) [10] and the DOI by Rogers (2003) [11] are frameworks that can be effectively applied in the context of adopting AI/ML technologies. The findings of this study are consistent with the frameworks emphasizing on the importance of technological readiness in terms of a comprehensive strategy on data, organizational moorings in the form of leadership will and drive to adoption of AI / ML technologies, creating a culture conducive to adoption of change and new workflows and external factors such as competitive forces, regulatory norms compliance and digital assets security and safety. The TOE focus is at an organisational or industry level, and the DOI primarily deals with the adoption of innovation at the individual level. Both TOE and DOI are relevant in the context of this study as decisions related to investment, use case are within the context of the organization whilst the acceptance of the AI / ML technologies is at the individual level where the applications come to life and produce tangible outcomes in terms of efficiencies, cost savings, low to negligible variability in the final product. Hence, both TOE and DOI are relevant and helpful in gaining an understanding of the adoption of AI / ML technologies.

In this study, there are a total of 23 respondents aggregated between the 4 semi-structured interviews and 2 FGDs in which 19 employees participated. They represent employees from Oil and Gas, Petrochemicals, Polyethylene, and Automotive Tire manufacturing. Each of these are process industry that deploys differing technologies and provides diversity in manufacturing processes and systems as well as end products. The current study can be expanded to other industry groups, such as Fast-Moving Consumer Goods (FMCG), Automotive Component Manufacturing, and similar sectors. This is a limitation of the study. A broader industry representation could strengthen the findings.

The process industry faces several unique barriers to adopting AI technologies. One of the primary challenges is ensuring data quality, particularly in terms of completeness, accuracy, and consistency, when integrating information from legacy systems. Closely related is the issue of data governance and ownership, which requires clear accountability for data quality, inclusion of data governance in budgeting processes, and the assignment of responsibility for maintaining quality in deployed AI applications. Another significant barrier is the need for a change in mindset and training—transitioning employees from traditional, rule-based operations to a data-driven, AI-focused model demands ongoing education, cultural change, and upskilling across the organisation. Data privacy and security also pose critical concerns, particularly in complying with legislative and regulatory requirements during the collection and analysis of sensitive industrial data. At the same time, the evolving regulatory landscape compels organisations to continuously adapt their practices to stay compliant with new and emerging standards concerning data privacy and security.

Conversely, several enablers support the adoption of AI in the process industry. One of the most fundamental is recognising data as a business asset, which promotes a shift from a purely technology-driven outlook to a business-focused approach where data is utilised to solve specific challenges and generate measurable value. Another key enabler is the deployment of AI to tackle specific business issues, such as reducing scrap, increasing throughput, optimising energy use, and improving safety performance. Cloud computing and edge devices also play a crucial role. While cloud computing has revolutionised scalable infrastructure, there is a growing need to boost computing and storage capacities on edge devices to facilitate real-time decision-making and lower latency in operations. Moreover, partnering with technology providers—including system integrators, cloud platforms, and specialised AI vendors—allows organisations to access customised AI solutions and reliable infrastructure. Leadership commitment and vision significantly accelerate AI adoption, fostering a culture of innovation, experimentation, and data-driven decision-making. Finally, employee enthusiasm and skill development, especially among younger generations, lay a strong foundation for adopting new technologies. Offering employees opportunities to learn and develop reinforces their engagement and underpins the successful implementation of AI. Overall, these barriers and enablers present a comprehensive view of the critical factors influencing AI adoption in the product and process industries, reflecting the distinct challenges and promising opportunities within this sector.

From a practical standpoint, the study provides recommendations to organisations as follows: investment in data infrastructure to maintain the integrity of data throughout the capture, synthesis, storage, retrieval, and comprehensiveness processes, enabling its use in algorithms. Mathematical modelling for a purpose is the most important aspect of data management [16]. Organisations need to nurture a culture of fearlessness, thereby promoting risk-taking abilities in trying new and different approaches to institutionalise a culture of innovation and entrepreneurship. New ways of working (WOW) need to be a part of the routine way of functioning to harness synergies within and across functions in the organisation. All functions need to be aligned with the ultimate organisational goals to be unidirectional and eliminate scattering of resources. Digitalisation presents a significant opportunity for fostering high employee engagement by offering opportunities for learning and growth. These actions collectively help break down resistance to change and support the assimilation of new technologies and innovations, [26 - 28].

Regulatory norms are intricate and must be navigated skilfully, as they ultimately enhance security and safety for technological assets [50], [29]. The ability of leadership to articulate a compelling vision for AI / ML adoption fosters alignment of ideas within the organisation by providing clear direction. Such direction clarifies goals and suppo in the appropriate allocation of resources. It ultimately enables the achievement of objectives that generate value for the organisation, evident in financial performance, customer experience, and sustainability metrics [51]. The organisations involved in this study are multi-billion-dollar entities; fundamentally, the process of adopting AI/ML technologies does not significantly differ based on organisational size. Every AI / ML implementation must align the use case with organisational strategy, followed by a thorough examination of the data framework needed to enable the algorithm, which in turn influences technology requirements such as computing power, data storage capacity, and whether to utilise cloud, on-premises, or edge computing based on the end use. Moreover, leadership challenges and drive are not variables that depend on organisational size when adopting AI/ML technologies. Therefore, as noted above, the dynamics of AI / ML adoption remain largely consistent. Most government agencies and regulatory authorities worldwide support AI/ML adoption through incentives or infrastructure assistance, as this ultimately impacts the competitiveness of the industry and commerce within the country, serving as a source of competitive advantage at the national level.

The findings in this study contribute to the growing body of knowledge and literature on the adoption of AI/ML technologies. Critical, selective, and prudent investments in use cases that yield significant ROI should be adopted first, as they change the organisational dynamics and reinforce trust in AI/ML technologies as an enabler. Ultimately, behind every single AI/ML technology is the human mind, and that human mind is becoming better at using technology judiciously, such that it transforms both the organisation and the individual. However, another aspect that requires careful attention is establishing trust in data, facilitating the sharing of data across various functions/departments, and creating a data framework that is universally applicable and useful. Proven results enable the acceptance of new technologies and support the overcoming of issues such as working in silos, trust, sharing data, and the like. In the ultimate analysis, once proven results are achieved, it inspires the workforce and fosters leadership's confidence in having made the correct decisions.

Acknowledgement

The authors would like to express their deep gratitude to all the study participants, who not only found time within their day jobs to participate but also discussed in detail follow-up issues that required clarification from the initial interactions.

Declaration of conflict of interest

This research paper is original work of the author(s) and the same has not been published earlier in any other publication. None of the authors has any previous knowledge of participants in the four organisations who participated in the study.

Funding

No funding has been received from any organisation or agency.

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