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Bridging Business Transformation and Data Engineering for AI-Ready Enterprises

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ABSTRACT
Organizations are realizing the importance of value generating business transformations to remain competitive. With the rapid progress of the digital world, business transformation are not only desirable but essential. Integrating Artificial Intelligence (AI) and data across business functions is pivotal to this transformation. However, integrating residential data engineering competencies is vital to ensuring organizations are adequately prepared to scale and operationalize AI. This paper explores the intersection of business transformations and data engineering to make organizations AI ready. It illustrates how the engineering of data – with emphasis on data pipelines and governance, and architecture – to enable seamless, scalable, and AI-powered ecosystems, should run in tandem with pivotal business strategies, organizational change, and technological advancement. The paper integrates the literature regarding the transformation of the business, engineering of data, and the adoption of AI, identifying the key barriers and enablers, and presents a conceptual model integrating these fields. It also presents a plan to assist organizations in successfully integrating the engineering of data and transforming the business to make organizations ready for AI. The paper ends by outlining the practical consequences for organizations and the possibilities for further studies in this area.

Keywords: Business transformation, Data engineering, AI readiness, Digital disruption, Organisational change

I. INTRODUCTION

Organizations are dealing with interconnected pressures in this rapidly persistent digital world. The digital economy, in which firms must innovate more frequently to stay ahead, is one of these interconnected pressures. Additionally, they must address the rising expectations of customers for real-time and individualized experiences, the growing potential of Artificial Intelligence (AI), and the possible advancements in efficiency, innovation, and decision-making. In the business context, the implementation of AI is a long and difficult road. The primary problems are capturing and integrating AI into a business' activities so that it is more than an isolated usage and is instead a part of the business routine. This involves a combination of solid data infrastructure, advanced engineering practices, and the strategies and culture of the organization.Recent studies show how companies like McKinsey and Company show how companies utilizing artificial intelligence as a large percentage of their business as extremely enthusiastic and have tried to incorporate artificial intelligence into their business as a tool to increase their profit and productivity and work smarter and not harder . Unfortunately , due to a gap in vision the integration of artificial intelligence into their businesses becomes stalled and without success. Businesses begin the artificial intelligence models to show promises of success, however, move quickly to stagnation and businesses quickly lose interest in the models. Problems and stagnation of models stem from a businesses dysfunctional collection of data, and a focused gap in their models to have a business, tech and operational processes balance and focus. The next step to success in business is to incorporate artificial intelligence into business models and continue to be adjustments to be operational with goals to accomplish.This study aims to illustrate the impact of data engineering and business transformation striving efforts and how they can be used to shape truly AI-ready enterprises. The term \\"AI readiness\\" describes an organisation which possesses the right amount of data, an adequate level of technology, appropriate governance frameworks, precise processes, and a culture of management which allows the seamless deployment, management, and maintenance of AI systems, as well as the evolution of those systems. This means more than simply modernising technology and managing data. It involves a shift within the organisation that focuses on synchronising the capabilities of AI with the strategic objectives and culture of the organisation.The second part of the paper discusses the relevant literature concerning the business transformation, data engineering, and incorporation of AI. This includes the construction of the bridging conceptual

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framework, the encompassed variables, and the intersection of the variables that make AI readiness possible. Next, also analyze the case studies and provide empirical evidence that assists in understanding the main facilitators and obstacles to the adoption of AI. This is followed by the provision of a practical guide in order to aid the practitioners to achieve the transformation of the business processes by the incorporation of data engineering within the organization, and in turn become AI ready. Lastly, the paper discusses the possible implications of the obtained results along with the suggestions for the further research initiatives that need to be undertaken within the organizations.

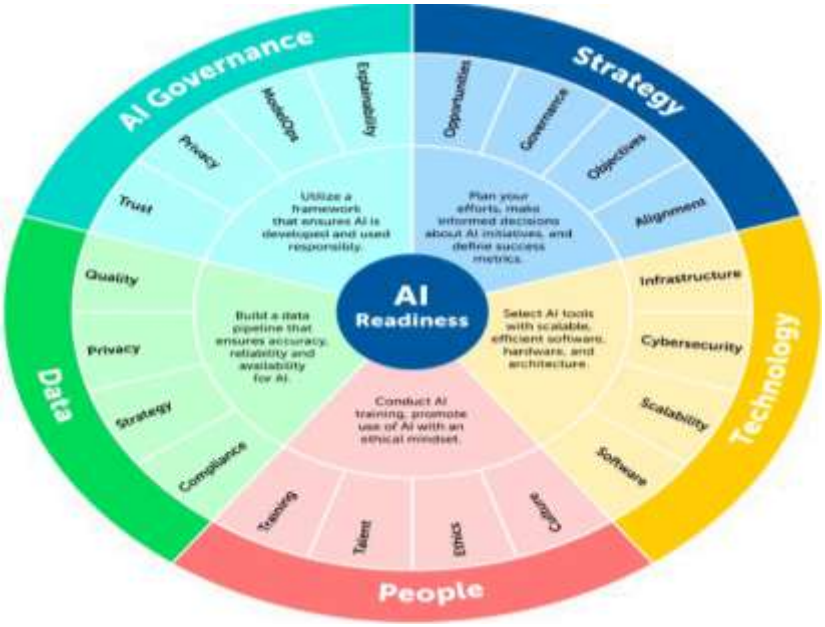

Figure 1: AI Readiness Framework: The Convergence of Business Transformation, Data Engineering, and AI Deployment.

2. Literature Review

Business Transformation

Business transformation is about making drastic impacts on how an organization works to offer better performance, improvement, and competitiveness [1]. In AI driven business, technology implementation is not enough; it demands a comprehensive rethink of business models and workflows, along with a cultural alignment to digital and data centric [2]. Given the intricacies and interactions involved in AI, organizations have to align strategy, talent, operational models, technology, and data with the greatest precision. Process innovation and AI adoption entail a reconfiguration of processes and the stewardship of leaders who can create a context in which infrastructure can be adapted to support a non-stop cycle of digital transformation and AI Diffusion [3].

Data Engineering

Data engineering is foundational to the realization of any AI system through the establishment of systems that design and manage data [4]. Data engineering's main tasks of data capturing, intergration, transformation, warehousing, construction of data repositories, and data quality maintenance fuel the AI applications that need accurate, reorganized, and timely data [5]. AI models will be limited to ineffective data, non-cohesive datasets, and suboptimal systems in the absence of refined data engineering [6]. This will limit the models capabilities. Proper data engineering allows for the unencumbered flow of data to be processed in other systems [7].

AI Readiness and Enterprise Adoption

There are obstacles to large-scale AI enterprise adoption on both the technical and organizational fronts [8]. Many companies continue to have difficulty proceeding from pilot projects to fully operational AI, and success in scaling AI is not easy. Some of the key factors are active support from top management, alignment of AI project goals with substantial business value, adequate organizational competence in data and technology, and proper utilization of human resources [9]. Organizations must have the right technical resources in place, but they also must cultivate an environment that is open to the restructuring of business processes and the introduction of innovative ideas. The ability to successfully implement AI solutions is predicated on the cooperation of organizational and technical aspects [10, 11].

Bridging the Domains: What the Literature Suggests

According to the business literature, there is a noticeable disconnect between the strategy/plan for the business

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transformation in the literature and the implementation of the technology and data engineering [12]. Most failures in the adoption of AI are a result of businesses not closing the transformation to technology gap [13]. Literature is starting to suggest one of the answers is the merging of the business semantics with the data engineering systems so that the data architecture is aligned to fit with the business goals [14]. Additionally, the function of data engineering is no longer just an IT function; it is also a strategic driver of business value, meaning that organizations need to consider data engineering as one of the fundamentals of their business strategy [15]. However, there is a shortage of research that integrates these fields in order to provide a clear pathway that associates the transformation with the requisite data engineering for the implementation of AI. This gap in the literature justifies the design of a conceptual framework that integrates these fields to promote the effective use of AI.

3. Conceptual Framework: Bridging Business Transformation and Data Engineering

The work outlines a cohesive framework which connects these three domains, critical for achieving the AI readiness of enterprises, namely, Business Transformation (BT), Data Engineering (DE), and AI-Ready Enterprise (AI-RE). The framework aims to demonstrate the interplay and interdependencies of the domains that are critical for the effective deployment and scaling of AI.

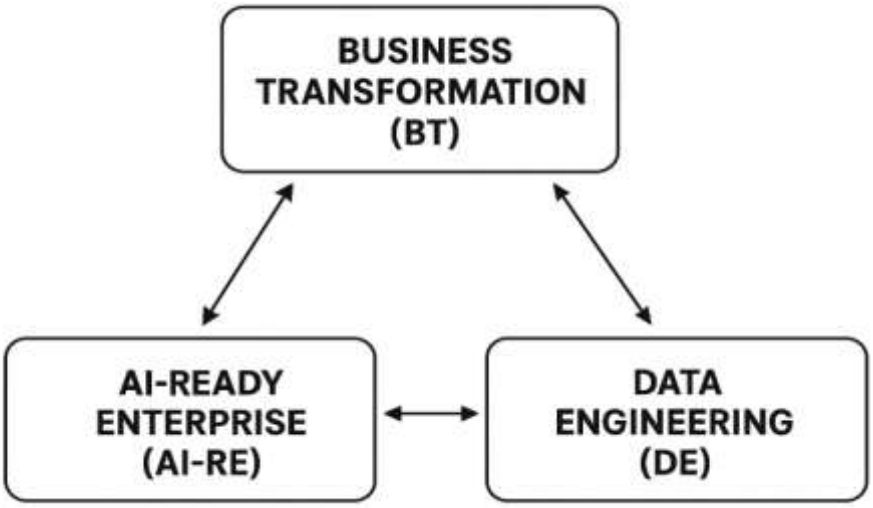

Figure:2 Conceptual frame work

Domains and Components

Business Transformation (BT)

Business transformation (BT) improves performance and enhances innovation in an organisation by fundamentally changing how it operates in terms of its structure, culture, and technologies. At its core, BT is about integrating an organisation's mission, vision, and business objectives with new technologies, markets, and models. The main components of organisational BT include a culture and structure of continuous improvement that allows employees to be flexible and adapt to new processes and ways of working. Redesigning processes to include new technologies is critical to performance optimisation. A value proposition is a core element of a company’s business model, specifically with the acquisition of new AI technologies. The company requires strong leadership with adequate people management to enact these changes to the company which include the building of skills and competencies within the company and assisting the upper management with the organisations change.

Data Engineering

Data engineering (DE) involves the design, construction, and upkeep of systems for the collection, storage, processing, and analysis of information. In an AI-centric company, DE becomes indispensable for constructing the architectural foundations necessary to efficiently manage large quantities of information with regard to data quality and consistency. The data engineering subsystem that deals with the value and the quality of data to be processed and stored and is therefore, the backbone of the data governance, is called data architecture and infrastructure. Systems for data pipelines and ingestion are required to acquire and prime data from diverse sources for subsequent analysis. Effective integration and synthesis ensure that isolated data sets are transformed into a singular, coherent resource for analysis. In the contemporary business environment, the ability to analyze and process information without delay is an important measure of competitiveness, and therefore, instantaneous and streaming data processing are indispensable. Operational reliability, alongside scalability, contribute to the capacity of modern data engineering frameworks to support an uninterrupted and systematic flow of data.

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AI-Ready Enterprises (AI-RE)

AI-Ready Enterprises (AI-RE) represents the culmination of the successful marriage of business transformation and data engineering. AI-RE is an enterprise in the current state of the technology adoption lifecycle where the firm is able to implement, govern and operationalize AI solutions at scale. More generally, this involves the embedding of AI across the firm's business processes and the embedding of AI models into the quotidian activities and decisions of the firm. In order for the AI models to be consistently accurate and relevant, there must be the capability for oversight and management of the models. The value of AI in business must be evaluated in order to assist the firm to assess the positive impacts of the AI in business and the innovative changes in the performance of the business. The continuously evolving environment, technology changes and the business needs will necessitate the need for improvement in the AI models. In order for an enterprise to be fully AI-ready, there must be the requisite technical architecture, fitting governance structure, and a culture of data informed decision making and relentless improvement.

Interactions and Pathways

BT ➜ DE

The understanding of the Bridge Theoretical Framework Business Transformation and Data Engineering is the first building block of the AI Ready Enterprise. Transformation efforts require a data strategy in order to maintain alignment with business goals and objectives. This requires determining how data drives business value, the data strategy, building the right roadmaps, and resourcing accordingly. If this alignment is missing, data engineering efforts are likely to be siloed or misaligned with business priorities, which will impede the ability to successfully implement and scale AI. The stronger the connection between business transformation objectives and data engineering, the better the organisation will be at building the right infrastructure and processes to support future AI capabilities.

DE ➜ AI-Readiness

Data Engineering is the basis for AI-Readiness. Effective data engineering construction is necessary for AI systems to operate and scale across the firm. Clean, integrated, and timely data pipelines are essential for AI models to provide and sustain the high-quality data. The value and the accessibility of data determine the performance of AI systems and the reliability of these systems. Hence, effective data engineering is the prong of AI systems. Moreover, the elasticity of data engineering systems ensures that as the growing organization and AI projects data engineering systems are capable of tremendous systems.AI – RE ➜ BT

AI's prevalence across business sectors results in further evolution of business processes, functions, employee roles and workplace culture. This self-perpetuating system enables constant evolution of businesses. Adoption of AI tends to alter the ways work is accomplished, decisions are made, and the skill sets required. For example, where work is characterized by repetitive and mundane tasks, AI systems can automate such tasks to allow the human employee to deploy effort and time in higher value, strategic and creative tasks. In such a work environment, other elements of the organization are required to adjust in response to the new ways of working. AI systems eliminate guess work and provide insights that can inform business strategies, create new opportunities, and adjust the market. As a result, AI Adoption benefits the organization and increases the pace of transformation of the organization’s business model and processes.

Framework Visualisation

Imagine a triangle with Business Transformation (BT), Data Engineering (DE), and AI-Ready Enterprise (AI-RE) at each point. This is how these domains are connected. The arrows point to how one domain affects the next. For instance, business transformation drives data engineering, and data engineering fuels the AI-Ready Enterprise. The AI-Ready Enterprise spurs new business transformation. Each domain affects the direction and the pace at which the others are moving, adapting a seamless loop of interconnected improvement.

and also suggest maturity stages for organisations moving from basic data awareness to AI readiness. These are:

• Data-Aware: The organisation understands data, but because of strategies and infrastructure gaps, data is left on the table.

• Data-Enabled: The organisation has set up data pipelines and data governance, but access to AI for decision-making may not be present.

• AI-Producer: The organisation has scaled AI at operational levels and is iteratively improving business outcomes on a continuous basis.

These maturity stages embody the shift from solid data engineering to full AI readiness, allowing organisations to build new strategies and capabilities on the move toward becoming AI-Driven Enterprises.

4. Roadmap for Practitioners

Based on the conceptual formulation above, and put forward a sectioned approach for firms seeking to merge

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business innovations with data engineering to transition to AI-enabled. This outlines the sequence of the AI assimilations to business functions, while detailing and streamlining the fundamental technical, managerial, and tactical components for the effective widespread application of AI.

Evaluating Data Engineering and Digital Transformation

The first milestone on the roadmap the entity's comprehension of the this intersection and the desired state of the entity's overall Digital Transformation Strategy. Understanding the Entity's Business Strategy and Value Drivers. The Entity must understand their Digital Maturity, their AI Assimilation, and their Data Infrastructure. Understanding the State of Data Engineering in the Organization is as critical as understanding the Current Data Pipelines, Data Governance Architecture, and the Data Team's Competencies. This Evaluation will serve to determine the gaps between the the current and the desired states. The final step in this phase is to ascribe the state of Desired AI Maturity. Organizations must have precise Business Value Hypotheses, AI Use Case Flows, and AI Scale use case aspirations in order to achieve Alignment and Synergy on the business goals. This phase will serve as the foundation for detailed planning and action in the subsequent phases.

Strategy & Alignment

In the Strategy & Alignment stage, the organisations must articulate a data strategy that meets the objectives of the business transformation. This ensures that data initiatives become an integral part of the business as well as AI readiness. At this stage securing sponsorship from the leadership and governance structures is essential as the strong leadership commitment and explicit governance would steer the prioritisation of AI and the allocation of resources. At this stage organisations must also define primary business use cases for AI, targeting select focus areas that prioritise value and measurable impacts. Measuring success on the identified business initiatives will depend on establishing clear and measurable business KPIs. A data engineering roadmap is also required detailing target architecture, data governance, and necessary enhancements on existing data pipelines to support AI solutions.

Build Foundations

The focus of the Build Foundations stage is the necessary technological substruc-tures for AI applications. Within this stage, organisations can either build or refurbish their data architecture by adding data lakes or data warehouses, elastic storage systems, and the use of public, private, or hybrid clouds for big data. Perhaps one of the most pivotal facets of this stage is the construction and deployment of data streaming and batch capture pipelines. This is necessary so that organisations can process and deliver the diverse and often real-time streams of data required by AI models. In addition to the construction of data pipelines, organisations must also establish a comprehensive data governance framework, which must include reliable and secure systems for metadata, data lineage, access and control, and quality measurement. This stage should also see the commencement of AI model support feature engineering and data asset cataloguing to ensure that the required data assets for the construction of AI models are present.

Pilot AI & Embed in Processes

During the Pilot AI & Embed in Processes stage, organizations should begin focusing on the implementation of AI/ML use cases aligned with their corporate strategy. These pilot use cases should be focused on the specific business issues that demonstrate use of AI's value: customer churn prediction, predictive maintenance, etc. During this stage, businesses must ensure that they integrate AI into their operational business workflows. AI-driven outputs should be integrated into the business systems. AI must be operationalized by embedding AI into the operational business processes. Impacting these operational business processes by AI should be measured. Changes in business processes must be focused on the primary AI targets of cost reduction, revenue generation and operational efficiencies. The employee training required for these business process changes must be focused on the change management required in the business processes to integrate decision making with AI. This sets AI integration into operations and prepares the organization for making these solutions operational at scale.

Scale and Operate

Once the pilot projects have demonstrated success, the subsequent stage is to scale and operationalize the AI solutions across the enterprise. In the Scale and Operate stage, organizations need to incorporate MLOps pipelines to automate the deployment, monitoring and retraining of AI models. In this stage, model drift management, where models need to be updated timely to adjust to new patterns in the data is another consideration. The data engineering infrastructure must be able to support scale, ensuring real-time data ingestion and elastically scalable infrastructure is configured to meet demand. The governance interface should be expanded to include model fairness, ethics, compliance and auditability to ensure the AI systems are exercised in a responsible and transparent manner. A positive organizational culture of continuous data-driven innovation should be fostered in this stage to support feedback loops, experimentation and the adoption of emergent AI technologies.

Maintain The Same Updated Process.

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Continuing business rescaling using AI tools derives improvements in the organisations' business transformation strategy frameworks. It requires incorporation of additional models and processes from further applications of AI. In order to optimise the data infrastructure of the organisation, data engineering pipeline indicators of latency, data quality and data pipeline utilisation need to be observed. The same goes to the AI engineering indicators and model accuracy – they will be informative in guiding the organisational planning in investments, thus prioritising AI initiatives that will yield competitive ROI. Agility is the key in this step as organisations need to catch up with the new generative AI, AI agents and semantic systems. Layering data-centric governance systems with multidisciplinary team structures will enable organisations to deploy their transformation efforts to AI. That, in turn, will allow organisations to further enhance their competitive and sustainable edge.

5. Results and Discussion

This section explains what the research showed and considers the implications of the findings with respect to the conceptual framework and the strategy for integration of the business transformation and data engineering for AI readiness. The results concentrate on the foundational elements of the framework and these are business transformation, data engineering, and AI readiness. Also show the ways in which these concepts have been successfully blended by different organisations and the wins and loses in the attempts by various companies to achieve the integration of business transformation and data engineering to achieve AI readiness.

Results

To assess the degree of validity of the proposed framework, and carried out a number of case studies of organisations at different stratum of AI adoption. The main goal of the case studies was to determine how organisations are progressing in the AI readiness journey, particularly the transformation of the business and how it relates to engineering activities. The case studies yielded the following results:

• AI Adoption Maturity: The organisation s at the lower levels of AI adoption were what term as data aware, in other words, they recognised the importance of data but there was no significant level of data engineering frameworks. These organisations was highly limited in their ability to scale AI because of siloed data and poor data governance.

• Integration of Data Engineering: Enterprises that were advanced in their AI journey were data enabled, with configured data architectures and data governance frameworks in place. AI operationalization challenges and gaps still remained, predominantly from the lack of interweaving of business transformation and data engineering operational practices.

• Business Transformation & AI Alignment: Alignment of business transformation in most organisations was substandard, coupled with the lack of enthusiasm for AI, there was also a disconnect between business goals and the technical infrastructure needed to operationalise AI models. The case studies have shown that the most successful organisations defined AI scenarios that were closely tied to business KPIs and subsequently realigned their data engineering frameworks to optimise for those scenarios.

• Scalability Challenges: The lack of scalable AI solutions was a bottleneck for most enterprises, including those with a matured data engineering practice. The absence of operational data streams that support the agile movement of data at scale and in real time needed to be addressed.

Discussion

From the case studies, there exist a multitude of lessons that organisations can employ to narrow the gap between business transformation and data engineering for AI readiness.

Business Transformation and AI Readiness

There have been multiple instances where the right AI infrastructure was set up and showed promising results. However, the AI infrastructure failed to show success in the long run due to a lack of alignment with the business transformation. AI was strategically placed as a business asset and not just a technology. This emphasizes the need to transform the business to accommodate AI with a shift in culture, processes, and leadership.

This is also supported by the provided case studies where the leaders of the organization were committed and were able to strategically align AI with the business objectives. They also gained the required organizational sponsorship and were able to transcend the cultural and organizational constraints. They recognized the need to integrate AI into the organization sustainably and not aim for quick wins.

Data Engineering: A Critical Enabler

Having advanced data engineering capabilities such as data engineering, real-time data processing, data quality management, etc. are crucial for organizations to effectively deploy AI models, as confirmed by other studies. That said, many organizations, even with advanced data engineering capabilities, still struggled to achieve desired scaling of their AI solutions.

Our case studies highlighted the integration of business transformation with data engineering, and the challenges therein. Even though organizations made considerable investments to build their data infrastructure, these

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investments were often isolated and did not tackle the business problems the AI was designed to solve. For instance, data management and business teams operated in silos: the former focused on crafting advanced technical systems while the latter worked on the AI use cases with little to no KPIs in place. This misalignment was a clear indication of the need for improved collaboration between the business side and the technical side.

Operationalizing and Scaling AI.

In this final stage of AI adoption, the scalability and operationalization of AI solutions remain the greatest challenge for organizations. The case studies under review have shown that organizations face struggles in scaling the application of AI even with excellent data engineering. This is due to the limitations of the engineering infrastructure in real-time data processing and scalability of infrastructure.

For predictive maintenance, customer engagement, and more, real-time data ingestion is essential. Organizations that could not keep infrastructure that supported real-time and high-velocity data streams experienced difficulties in gaining real-time insights. This was especially the case in manufacturing and retail. These sectors struggled with AI as it was required to function at scale and with little latency for significant economic benefits to be realized.

The Case Studies on Continuous Transformation

The case studies brought to the attention the importance of constant change for the AI-readiness of organisations. Those that managed to change their data engineering and business transformation practices showed better adaptive capacity to the evolution of market and technological changes. AI readiness is not a final destination, but a constant adjustment of the business models, data infrastructure, and AI models. Those organisations that adopted this philosophy were the ones that gained the most substantial benefits on AI.

Tables and Visual Representation of Results

Table 1: AI Adoption Maturity Stages

Stage	Description	Key Characteristics
Data-Aware	Organisations recognise the importance of data but lack the infrastructure to leverage it.	Fragmented data sources, basic data awareness.
Data-Enabled	Organisations have established data architectures and governance but struggle with AI integration.	Integrated data pipelines, basic AI use cases.
AI-Producer	Organisations have scaled AI solutions, integrated into workflows and generating business value.	Scalable AI models, clear business KPIs.

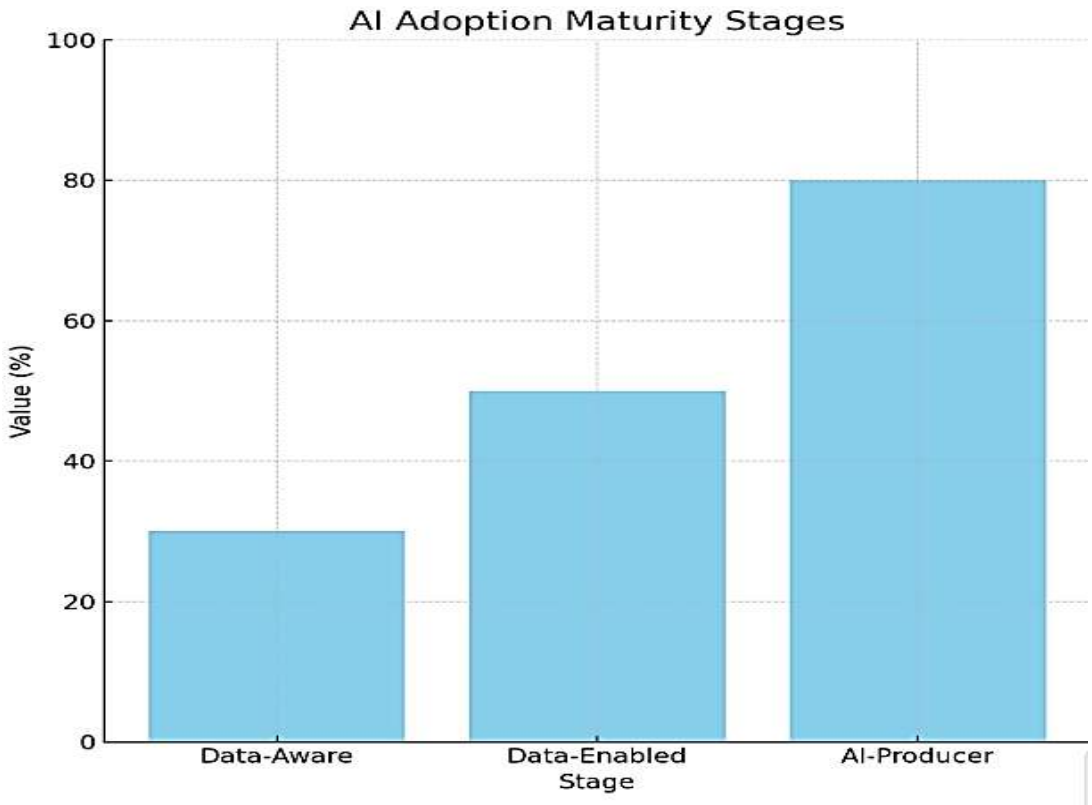

Table 2: Key Challenges in Scaling AI

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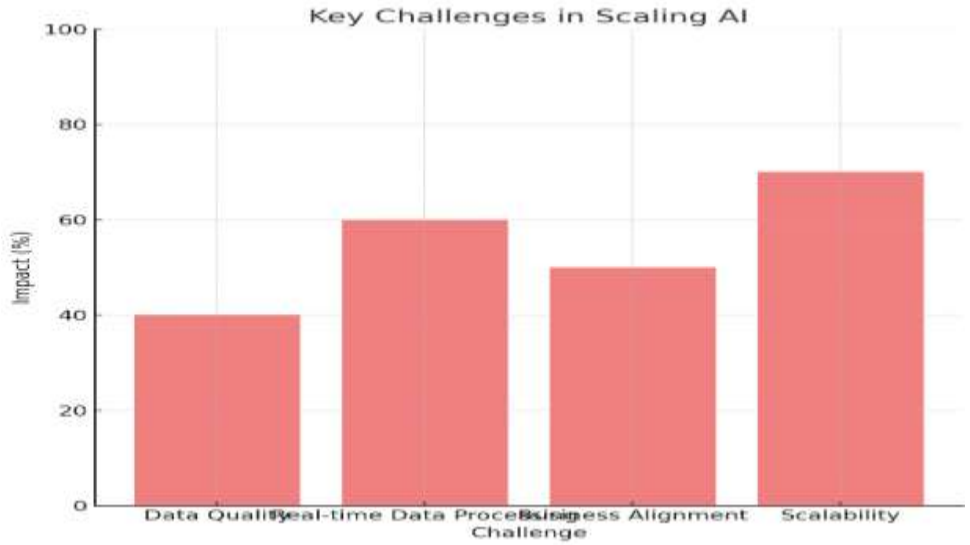
Challenge	Impact	Solution
Data Quality	Poor data quality leads to unreliable AI models.	Establish strong data governance frameworks.
Real-time Data Processing	Delays in decision-making due to lack of real-time data.	Implement real-time data ingestion pipelines.
Business Alignment	AI projects not aligned with business objectives.	Define clear business KPIs and AI use cases.
Scalability	Difficulty in scaling AI solutions across the organisation.	Invest in scalable infrastructure and MLOps.



The studies illustrate the needed combination of operational flexibility with data engineering as the first step to AI readiness. Businesses must realize that AI is not a tech play; rather, it is a business strategy that should be integrated into the business core. For efficient AI deployment from the top of the funnel, intentional leadership, defined data strategies, and delineated AI use circumstances must be present. Besides these, deliberate investments should be made to address the perennial problem of AI deployment towards the agility to process data in real time and to scalable data architecture. If businesses are to embrace the self-propelling transformation that will allow them to be in step with the pace of improvement in technology, they, definably, need to maintain a balance of flexibility and robustness in the business.

6. Implications and Future Research

In this part of the paper, explain the possible consequences of our research, suggest potential new research questions, and present the constraints and shortcomings of our research.

Implications for Practice

This paper brings across the importance of understanding that achieving AI readiness consists of much more than a technical focus, and that the evolving and dynamic intersection of business strategy, organisation design, transformation, and advanced data engineering is a critical and fundamental synthesis. Understanding the importance of data engineering, organisations should seek alignment between business transformation objectives and data engineering investments, especially when organisations wish to integrate AI into operational processes. The organisations with the desired technology and infrastructure, risk falling short without the integration of data and a profound focus with the value proposition being pursued in the marketplace.The presence, successful, and sustainable impact of AI models will more or less bypass the organisation if advanced AI models fail to operationalise the pieces of a data culture, value and the business processes. More than design governance frameworks, the organisation needs to self-develop the organisational processes to fit, cultivate, and redefine the new driven processes. It is critical, to demonstrate that AI operationalisation should not be confused with a stand-alone technical initiative, which will only focus and constrain to a siloed value, but should be viewed as a powerful and critical enabler to the broader value of business transformation.Another practical implication involves the necessity of leaders concentrating on the cross-disciplinary partnership between the data and business units. For the success of AI adoption, business goals must steer the data strategy, and data engineering must assist the business in realizing its objectives. In addition, leaders must be able to handle the cultural and organizational shifts

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that accompany the integration of AI along with assuring that their members have the required competencies to engage with data and AI technologies.This text essentially argues that the given practice-oriented implications are such that the organisation must adopt an all-encompassing approach. It relates to the interconnection of business strategy and technology, the allocation of financial resources into data infrastructure, and the cultivation of a culture centred around continuous change, innovation, and data.

Research Potential

Although this paper presents a theoretical construct, whereby the integration of business transformation and data engineering in AI adoption is conceptualised, further inquiry is warranted to open up exciting prospects for future research.

Research on the Design of AI Adoption

One of the most fruitful prospects for future research is the implementation of empirical studies that track organisations as they progress through the stages of AI adoption, as outlined in the framework. Research could be directed towards understanding the attributes of organisations that are able to achieve success in scaling the deployment of AI, as opposed to those that are unable to do so. Such studies could illuminate specific organisational patterns, leadership behaviours, and/or sophisticated technologies that support the sustained scalable adoption of AI.

Cross-Sector Comparative Case Studies

Cross-sector case studies, for example, in manufacturing, banking, and healthcare, could shed light on the various ways the intersection of business transformation and data engineering is approached. Each industry may differ in the approach taken to integrate business transformation with data engineering, and this could provide more tailored recommendations within particular industries to the organisations that are adopting AI.

Advancement of Measurement Instruments

The tool development of measuring 'data engineering readiness' and 'AI readiness' is suggested for future research. Such tools would allow for organisations to evaluate where they currently stand and what they need to improve upon. There is the possibility of lagging positive value for the business to be derived from investigating the impact of such tools on business performance outcomes, which could help support the business case for the future adoption of AI and guiding the requisite data engineering and AI investments.

Advancement of New Technologies

As data engineering and AI continue to advance, opportunities to understand the impact of new technologies will become even more important. For example, agentic AI (which autonomously acts on data) and semantic business-data systems (which add meaning and context to data for the purposes of AI) are progressing quickly. Research in these areas will enable organisations to integrate new technologies more effectively into their AI activities, and advance their competitive and innovative positions in markets characterised by rapid technological change.

In particular, a business semantics-centered architecture for data systems, which assimilates business logic with data engineering. It would be interesting for future studies to examine ways to make such semantic systems be even more effective in bridging data, business strategy, and AI to achieve more enhanced AI readiness.

Workforce and Organisational Design

Research exploring workforce and organisational design, particularly how data engineering teams, business analysts, and change protagonists work together during business transformation, is also necessary. Gaining a clearer understanding of how these cross-functional teams work together could provide valuable guidance on how to better configure teams in order to speed up AI adoption within organizations. This research could also investigate what data engineers and business practitioners of the future will need to successfully implement AI systems.

Limitations

This document gives a theoretical instrument to connect business change and Data Engineering for AI-readiness, however, there are a few missing targets and boundary conditions that need to be clarified.

Absence of Original Primary Empirical Data

This document offers a theoretical instrument to connect business change and Data Engineering for AI-readiness, however, there are a few missing targets and boundary conditions that need to be clarified. Defining the scope of the problem proposed and the solutions should align the research within the most critical management scientific domain, moving across business management and data engineering. Clearly, and with a simplified research focus, documents, and contributions of authors should be expanded with original primary data to enhance the theoretical framework offered.

Rate of Change to Technology

The continuously greater change to technology, particularly to Cloud Computing, Edge Computing and Generative AI, changes the focus of the relevance of this framework. The greater the pace of change to technology, the greater

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the need to shift the focus to the engineering of data to accommodate the new AI tools and the strategies to engage AI within a business paradigm. In future works, and within this scope, the research should outline changes to the life cycle of adoption AI and focus to the gaps of the proposed framework.

Relevance to Small and Medium Enterprises (SMEs)

This paper is focused on big businesses. However, some parts might also apply to SMEs, but some modifications would have to be made. SMEs have a different set of issues such as less funding, smaller data teams, and fewer tech resources. There are no doubt a great many SMEs in emerging economies that would have to be researched in order to apply the framework to SMEs that have little to no access to sophisticated AI tech

Contextual Applicability in Emerging Economies

Lastly, the framework will also have to be modified to accommodate the peculiar issues and opportunities organisations in emerging economies face. In this context the availability of data, tech infrastructure, and talent is not the same as in the developed world. An important area for research is understanding the interplay of business transformation and data engineering in the context of emerging economies.

Conclusion

To sum up, this paper attempts to demonstrate the importance of organizations integrating of business transformation, data engineering, and organizational elements needed for achieving AI-readiness. With AI as an emerging technology in organizational business models and strategies, the successful adoption of AI technologies goes far beyond merely technical efforts undertaken in the building and deployment of models. Effective data and business engineering transformation must align to strengthen the organizational data architecture, governance frameworks and processes. This is what the discussed framework aims to support organizations in working towards building an AI-ready enterprise.The outcome of the case studies along with the discussion has pointed out that the readiness of organisations is complex. After years of study of technology, organisations still struggle with aligning efforts of AI with the other components of the business. There needs to be collaboration to merge the design of business transformation with engineering of data. And the extent of effectiveness of the initiatives of the organisations is also directly related to how well they manage to design engineering solutions of business to the problems of AI. Any organisation that achieves the engineering of business problems will achieve the design of AI with greater value and innovation spinning through various operations of the business. For practitioners, this paper reinforces the need to adopt a complete paradigm. Among other things, leadership, strategic alignment, and culture must be of equal importance with the data infrastructure, models of AI, and other technological tools. AI readiness must be viewed more than a technological advancement but as a core strategic business enabler with an emphasis to innovation, fundamental changes, and a sustainable competitive edge. This serves to inform scholars that the proposed model requires testing and empirical revisions; hence, the call for additional research targeting the integration of the potential technologies, selective industry examples, and workforce planning intricacies.

This research provides a model and sets a foundation for future work, particularly examining how organizations advance through the various tiers of AI maturity. Given the evolution of technology, the framework will require consistent modifications to incorporate advancements with AI, the cloud, and additional technologies. Maintaining adaptability and a systems thinking approach will ultimately set organizations apart during AI-enabled business transformation. These will be the organizations that integrate business strategy with data engineering and AI, learning continuously, and adapting to shifts in the business context.

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