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Methodological Approach to Assessing the Current State of Organizations for AI-Based Digital Transformation

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Abstract: In an era defined by technological disruption, the integration of artificial intelligence (AI) into business processes is both strategic and challenging. As AI continues to disrupt and reshape industries and revolutionize business processes, organizations must take proactive steps to assess their readiness and capabilities to effectively leverage AI technologies. This research focuses on the assessment elements required to evaluate an organization's current state in preparation for AI-based digital transformation. This research is based on a literature review and practical insights derived from extensive experience in industrial system engineering. This paper outlines the key assessment elements that organizations should consider to ensure successful and sustainable AI-based digital transformation. This emphasizes the need for a comprehensive approach to assess the organization's data infrastructure, governance practices, and existing AI capabilities. Furthermore, the research work focuses on the evaluation of AI talent and skills within the organization, considering the significance of fostering an innovative culture and addressing change management challenges. The results of this study provide organizations with elements to assess their current state for AI-based digital transformation. By adopting and implementing the proposed guidelines, organizations can gain a holistic perspective of their current standing, identify strategic opportunities for AI integration, mitigate potential risks, and strategize a successful path forwards in the evolving landscape of AI-driven digital transformation.

Keywords: AI readiness assessment; business processes; data infrastructure

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1. Introduction

Artificial intelligence in the new world is not just a tool; it is the catalyst for a revolution. It is the dawn of a new era, where businesses do not just adapt—they thrive. This is the age of AI-driven metamorphosis, where the mundane becomes extraordinary and the extraordinary becomes the norm. In the contemporary landscape of global enterprises, the relentless pursuit of innovation is a cornerstone objective that drives organizations to strive for competitive supremacy and deliver unparalleled value to their stakeholders. Within this context, a transformative impetus emerges: the seamless integration of artificial intelligence (AI) into the heart of business operations. This convergence signifies more than mere technological advancement; it embodies a profound shift—an AI-based digital transformation [1] that reshapes the very fabric of how organizations function, decide, and engage with their stakeholders [2]. Imagine a realm where data speak volumes, where intricate patterns emerge effortlessly from vast data oceans, and where complex tasks are automated with finesse. This transformation is not just about embracing AI; it is about orchestrating a symphony of insights, automating intricate tasks, elevating customer experiences, and sparking the fires of innovation [3,4].

Digital transformation refers to the integration of digital technologies into all aspects of an organization, fundamentally changing how it operates and delivers value [4]. It involves rethinking business models, processes, products, and services to leverage the power of digital technologies, such as cloud computing, data analytics, the Internet of Things (IoT), and AI [5]. AI-based digital transformation takes this concept a step further by specifically focusing on harnessing the full potential of AI technologies to drive organizational change and achieve strategic objectives [6]. AI-based digital transformation represents a strategic approach that harnesses the power of AI to drive organizational change, deliver transformative outcomes, and revolutionize how organizations operate, make decisions, and interact with customers, leading to enhanced productivity, agility, and innovation [6]. By integrating AI technologies into business processes and systems, organizations can augment human capabilities, automate tasks, derive valuable insights from data, and make data-driven decisions [7]. This empowers organizations to streamline operations, enhance efficiency, optimize resource allocation, and create personalized experiences for their customers [8].

By leveraging AI capabilities, organizations can gain valuable insights from their data, automate repetitive tasks, and make more informed decisions [9]. This can lead to improved operational efficiency, increased productivity, enhanced customer experiences, and the ability to identify new business opportunities [10]. Moreover, AI-based digital transformation enables organizations to stay ahead of the curve, adapt to changing market dynamics, and drive innovation in their respective industries [11]. AI-based digital transformation presents organizations with unprecedented opportunities to revolutionize their operations, drive innovation, and deliver exceptional value to their stakeholders [12]. By leveraging AI technologies, organizations can unlock new insights, automate tasks, and make data-driven decisions [13]. However, successful AI-based digital transformation requires a holistic and strategic approach that considers technological infrastructure, data management, talent acquisition, cultural readiness, ethical considerations, and change management [14].

With careful planning, the right tools and infrastructure, and strong leadership, organizations can embark on a transformative journey that propels them into the era of AI-driven innovation and competitive advantage [15]. However, successful AI-based digital transformation requires the careful consideration of strategy, data infrastructure, talent, ethics, change management, partnerships, infrastructure scalability, and continuous evaluation [16]. Implementing AI-based digital transformation is not without its challenges. Organizations should carefully plan and execute their transformation journeys to ensure success [17]. They must consider several key aspects, including technology infrastructure, data management, talent acquisition, cultural readiness, ethical considerations, and change management [18]. The integration of AI technologies requires a strategic and systematic approach that involves multiple stakeholders across the organization [14].

This paper delves into a fundamental phase of AI-based digital transformation: evaluating an organization's existing state. The primary objective of this research is to offer a systematic and comprehensive approach for assessing an organization's readiness for AI adoption. By thoroughly examining processes, current technology infrastructure, data management capabilities, and overall organizational preparedness for AI integration [19], this study aims to identify gaps and constraints that might impede the successful implementation of AI solutions [20]. Special attention will be given to evaluating data assets, data quality, and data accessibility, which are essential foundations for effective AI-based initiatives [21].

The critical nature of this initial assessment cannot be overstated. It not only sheds light on the organization's strengths and weaknesses but also serves as the cornerstone for developing a strategic roadmap and efficiently allocating resources [22]. Through this meticulous evaluation, organizations can gain valuable insights into their technological infrastructure, data availability, organizational culture, talent pool, business processes, and regulatory considerations. Armed with this knowledge, organizations can make informed decisions, enabling them to embark on successful AI-driven digital transformation journey [23].

Significantly, the existing literature lacks a structured and holistic approach to assess an organization's current status for AI-based digital transformation, leading to fragmented insights and a lack of standardized guidelines. Our research steps into this void with a clear objective: to develop a methodologically robust and all-encompassing framework. To address this gap, this study provides a definitive methodology, thereby bridging the existing void in scholarly discourse. This research not only outlines the importance of assessing an organization's readiness for AI integration but also presents a robust framework that can guide practitioners and researchers in effectively conducting this critical assessment.

Our study provides practitioners and researchers with a tailored framework that offers specific methods for evaluating processes, existing systems, data landscapes, and internal AI capabilities. Unlike generic guidelines, our approach delves into organizational intricacies, ensuring a nuanced assessment. By considering system compatibility and human expertise, our systematic methodology equips practitioners to effectively identify challenges and leverage strengths. Our framework serves as a beacon in AI-based digital transformation, guiding organizations with confidence and efficacy through modern technological integration. It illuminates a clear path for organizations, providing them with the tools they need to navigate the complexities of modern technological integration. By offering a structured and holistic approach, we contribute not only to academic knowledge but, more importantly, to practical advancements, enabling organizations to embrace AI technologies with confidence and efficacy.

2. Materials and Methods

The research methodology followed in this work is described as "experience-driven" coupled with a literature review and represents a hybrid approach that marries practical, hands-on experience with a thorough exploration of existing academic knowledge. In this approach, our research draws extensively from the wealth of insights acquired through real-world experiences in the field of industrial system engineering. This practical knowledge is then complemented and contextualized by a comprehensive review of relevant academic literature. The "experience-driven" aspect of our research methodology suggests a focus on learning from actual situations, problem-solving in real-world industrial contexts, and understanding the intricacies of industrial system engineering through direct involvement and observation. This experiential knowledge serves as the foundation upon which our research is built, providing valuable insights that are often difficult to glean from purely theoretical perspectives. Simultaneously, our research incorporates a literature review component, indicating a meticulous examination of scholarly articles, research papers, and theoretical frameworks related to industrial system engineering. This literature review serves to situate our practical experiences within the broader theoretical landscape. This allows us to critically assess existing theories, identify gaps in the literature, and draw connections between academic concepts and real-world applications. By blending these 2 methodologies, our research is uniquely positioned to offer a holistic understanding of industrial system engineering. The synergy between hands-on experience and theoretical knowledge enhances the depth and richness of our research findings, allowing for a nuanced exploration of the subject matter. This hybrid approach not only strengthens the credibility of our research but also ensures its practical relevance, making it a valuable contribution to both academic scholarship and industrial practice.

Experience-driven methodology is not solely reliant on the collective experiences of the authors but is substantiated by their significant and varied professional backgrounds. These experiences encompass working in different geographies and cultural settings, thereby providing a rich diversity of practical insights. This diverse experiential knowledge base was integral to the identification of key elements in AI-based digital transformation, offering a multifaceted perspective that enriches our research. The authors' experiences were systematically reflected upon and recorded using a structured qualitative method, ensuring that subjective insights were critically evaluated.

Complementing the experience-driven approach, the literature review was conducted with methodological rigor. This review followed an explicit protocol designed to ensure the comprehensive coverage and systematic analysis of the literature. We employed databases such as IEEE Xplore, Scopus, and the Web of Science to collect relevant publications. Specific inclusion and exclusion criteria were applied, guided by the Preferred Reporting Items of Systematic reviews and Meta-Analyses statement for reporting systematic reviews and meta-analyses, to ensure the relevance and quality of the literature included. Keywords and search strings were carefully chosen to encompass a broad range of topics within industrial system engineering and AI technologies, and searches were confined to peer-reviewed articles published within the last 3 years to ensure contemporary relevance.

The selected references were chosen based on their citation index, relevance to the research questions, and the diversity of perspectives they offered. A thematic analysis was then conducted on the collated literature to identify, analyze, and report patterns (themes) within the data. This was essential to cross-reference the literature with the patterns observed in our practical experiences, thus ensuring a robust comparative analysis that bridges theory with practice. This approach can be summarized in the following diagram shown in Figure 1.

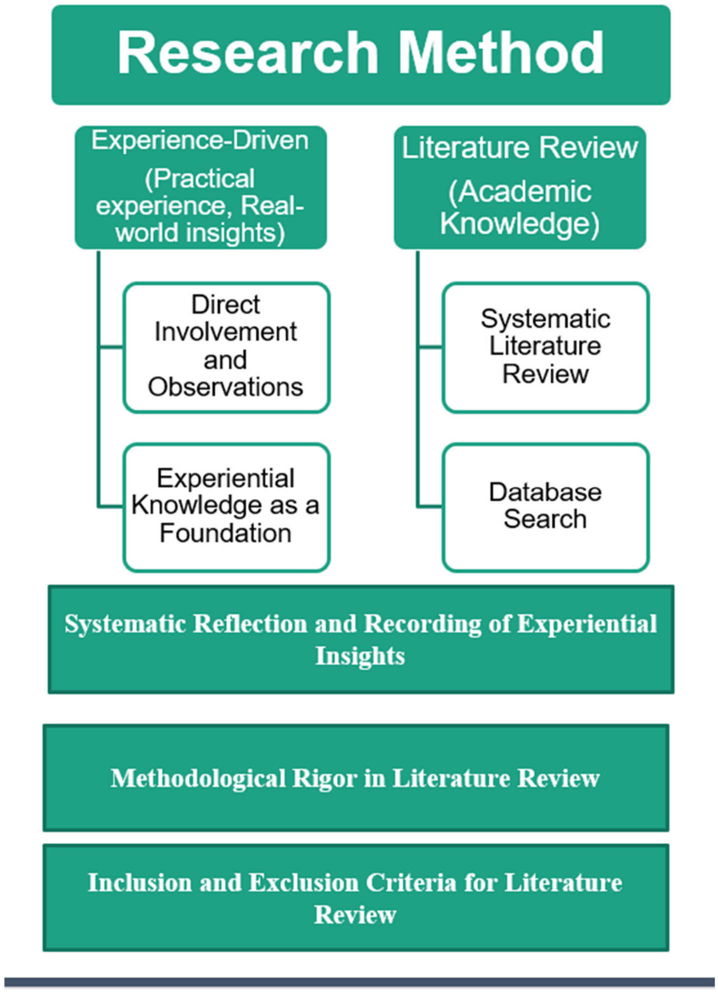

Figure 1. Diagram of research methodology process.

Assessing an organization's current state for AI-based digital transformation is a complex endeavor that demands a systematic and multifaceted approach. This approach involves the integration of various methods and techniques tailored to the organization's specific context and goals. By systematically integrating these methods and techniques, organizations can gain a holistic view of their current state in relation to AI adoption. In the development of our holistic guidelines for assessing an organization's current state for AI-based digital transformation, we meticulously crafted a framework encompassing four essential components: current process, existing systems, data landscape, and AI capabilities. Each element plays a pivotal role in evaluating an organization's readiness for AI integration, ensuring a comprehensive and informed approach to digital transformation. This comprehensive understanding forms the foundation for the informed decision making, strategic planning, and successful implementation of AI-based digital transformation initiatives. It is essential to provide a baseline to comprehend the organization's readiness for transformation, ensuring the effective planning and execution of AI strategies [24,25]. Figure 2 depicts the elements of the current state assessment. It allows organizations to assess their AI readiness, thus enabling the strategic allocation of resources for AI initiatives [26]. Here, there is a deeper exploration of the systematic approach that encompasses diverse methods and techniques in terms of the elements of current state assessment:

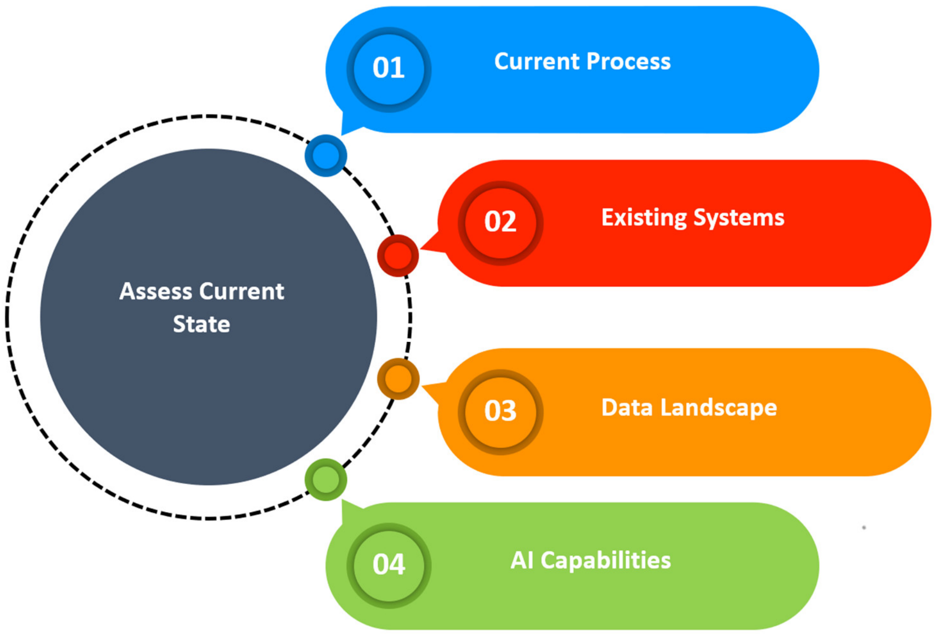

Figure 2. Element of current state assessment.

2.1. Current Processes

Current processes are the business operations and workflows that form the backbone of an organization's functioning. An in-depth understanding of current operations, workflows, and systems is essential for the successful application of AI. The work in [27] affirms that understanding the nuances of business operations and identifying areas that can benefit from AI are fundamental for enhancing operational efficiency. Understanding current processes requires at least the following:

Process Documentation:

The first step towards understanding the current processes is to have them thoroughly documented. This can be achieved by creating a process map or workflow diagram to visualize the steps involved, the roles accountable, the decisions made, and the systems used in each process. This documentation helps identify potential bottlenecks, inefficiencies, redundancies, and opportunities for process improvement or automation [26]. It outlines the sequential tasks required to perform the operational activities within a business. Once defined, these tasks provide an invaluable resource for understanding how work is carried out, who does it, the tools they use, and the outcomes they achieve [28]. It aids in identifying inefficient processes and potential areas for automation or improvement using AI technologies. Furthermore, it is essential for regulatory and compliance needs as well as in business process re-engineering, where the focus is on redesigning existing processes for greater efficiency or effectiveness [29]. The success of these AI-based tools heavily depends on the richness and quality of the data and how accurately it reflects the business processes.

Process Performance Measurement:

It is essential to have measures in place that accurately reflect the performance of the current processes. Key performance indicators (KPIs) should be defined for each process, capturing aspects such as the processing time, error rate, cost, and customer satisfaction. Tracking these metrics over time provides a performance baseline and can highlight areas where AI could add value [30]. This involves the identification and tracking of KPIs for individual processes, offering a quantifiable means to assess their operational performance and quality [30]. It can help identify areas of inefficiency, bottlenecks, or underperformance that could be addressed through automation, optimization, or redesign. Furthermore, this serves as a basis for the post-implementation comparison of AI solutions, making it possible to quantify the benefits of digital transformation in operational terms [31]. Various metrics may be employed. Common metrics include the cycle time, error rate, cost per transaction, process velocity, and customer satisfaction. It is increasingly common for businesses to use AI and data analytics tools for real-time process performance monitoring and analysis [32]. However, it is important to use relevant and balanced metrics to avoid creating unintended consequences. For instance, an overemphasis on speed might lead to a compromise in quality. Therefore, organizations must select metrics that provide a balanced view of the process performance [33].

Defining process KPIs is an essential part of the performance measurement and management. KPIs are quantifiable measurements that help organizations track their performance over time and achieve their strategic goals. Here, there are some steps to define process KPIs, as illustrated in Figure 3 [34,35]:

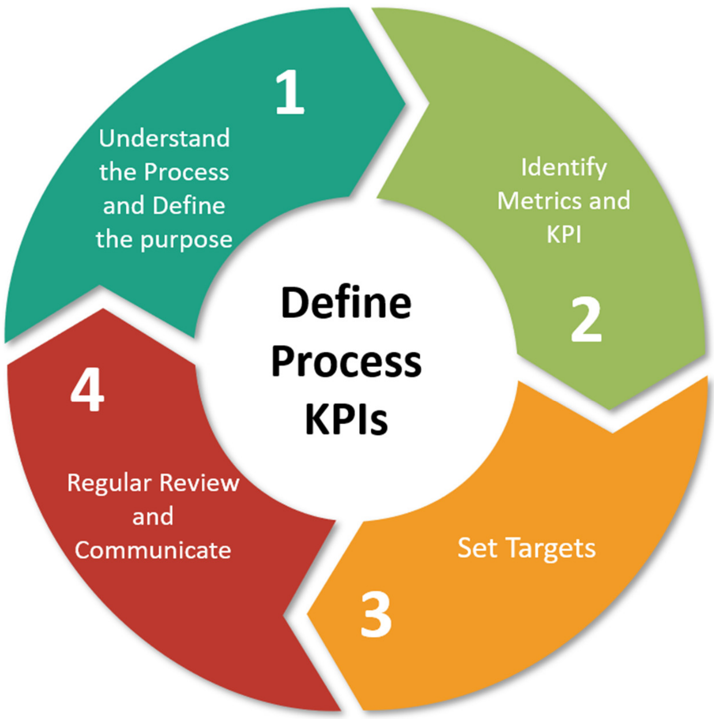

Figure 3. Defining process KPIs.

Understand the process and define the purpose: The first step is to fully understand the process that the organization is tracking. The organization needs to know what the process involves, its objectives, and how it contributes to the overall business goals [36]. The purpose of the KPI should be clear. This could be to increase efficiency, improve quality, reduce cost, enhance customer satisfaction, or any other objective tied to the business strategy [35,36].

Identify metrics and KPI: Identify metrics that best represent the process's performance and align with the organization's objectives. These metrics can be quantitative (like processing time, cost, error rate) or qualitative (like customer satisfaction) [35,36]. They can also be made to be S.M.A.R.T: the KPIs should be specific, measurable, attainable, relevant, and time-bound. This means that each KPI should precisely state what it measures, be quantifiable, realistically achievable, have a clear link to the strategic objectives of the business, and be bound by a specific time frame [34].

Set targets: Decide on targets for each KPI. These should be challenging but achievable. The targets serve as a benchmark for assessing the process's performance [35].

Regular review and communication: KPIs should be regularly reviewed to ensure they remain relevant and reflect any changes in business objectives or operating conditions. If a KPI is consistently being met, it may be time to set a more ambitious target. Conversely, if a KPI is consistently missed, it might be time to reassess whether the target is realistic [34,35]. Communicate the KPIs and their importance to all stakeholders, including employees. This helps ensure that everyone understands what KPIs are, why they are important, and how their role contributes to achieving them [34,35].

The process performance measurement, like process documentation, should be a continuous activity, with regular monitoring and updating to reflect the changes in the business environment, organizational objectives, or process redesign.

Process Automation Opportunities:

A careful analysis of the current processes can reveal repetitive tasks that are time-consuming and prone to human error, which are ideal candidates for automation. The use of AI can automate these tasks and improve the process efficiency. Moreover, AI can be applied to more complex tasks, such as decision making or pattern recognition, to further enhance the process effectiveness [37]. Identifying opportunities for process automation is a critical step in leveraging AI for digital transformation. Figure 4 illustrates the steps that can be used for business process automation as follows:

Step 1: Identify the Process and Define the Goals

The first step in automating a business process is to identify the processes that could and should be automated. Typically, processes that are repetitive, prone to human error, time-consuming, or important for compliance are good candidates for automation. By automating such processes, businesses can reduce the burden of mundane tasks on employees, leading to increased productivity and efficiency [38]. Determine what you want to achieve through automation. This could include improving efficiency, reducing errors, improving customer satisfaction, or other business objectives [39].

Step 2: Process Mapping

Understand and document the existing process from start to end. This step involves outlining each stage of the process, identifying who is involved, and identifying the tools used. This provides a complete picture of the current process and helps identify areas of improvement [40].

Step 3: Identify Automation Opportunities and Choose the Right Tools

Once the process has been mapped, identify which parts can be automated. It is important to consider which steps will yield the most benefit from automation because not all steps may be suitable or beneficial to automate [41]. Depending on the complexity of the process and business needs, the automation tool can vary. Tools can range from simple task automation software to more complex business process management (BPM) or robotic process automation (RPA) tools [42].

Step 4: Design, Development, and Testing of the Automated Process
Redesign the process by incorporating automation tools. Ensure that provisions are made for exceptions or error handling. It is crucial to have a clear process flow diagram that everyone can understand [43]. Once the process is designed, the next step is to build and test the automated process. This stage often involves IT professionals or consultants who have the skills to set up the automation and ensure that it works as expected [44].
Step 5: Training:
Before fully implementing the automated process, ensure that all involved parties understand how it works and their role in it. They should know how to interact with the automation tool, how to manage exceptions, and who to contact if something goes wrong [45].
Step 6: Implementation, Monitoring, and Continuous Improvement
After successful testing, roll out the automated process. It is often a good idea to do this gradually, starting with a pilot phase before full implementation [46].

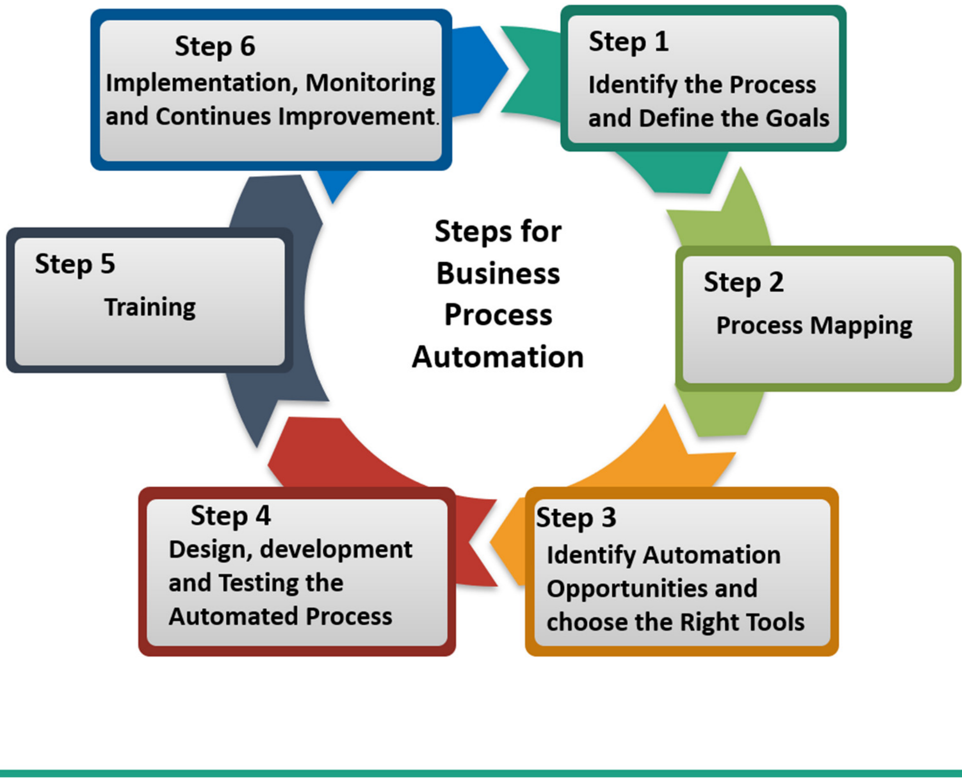

Figure 4. Steps to automate business.

After the process has been automated, it is important to monitor its performance to ensure that it meets its intended goals. Use the data from the automated process to identify areas for improvement and continually refine the process as needed [47].

The assessment of process automation opportunities needs to be carried out carefully, considering several factors. The complexity, frequency, and volume of the process are some of the aspects to be evaluated. It is also important to consider the cost, potential return on investment, and impact on customer service or other business functions [48]. Additionally, organizations should bear in mind that not all processes are suitable for automation. Processes that require human judgment, creativity, or complex decision making may not be ideal candidates for automation. Therefore, the assessment of automation opportunities should not only be based on the potential for efficiency gains but also on the strategic fit with organizational goals and values [49].

In recent years, AI-driven process mining tools have emerged as powerful aids for identifying automation opportunities. They can automatically analyze event logs from different IT systems to discover, monitor, and improve real-world business processes [50]. AI-powered technologies such as robotic process automation (RPA) [51] and intelligent process automation (IPA) [52] are increasingly being used to automate business processes. RPA involves the use of software robots or 'bots' to mimic human actions and perform repetitive tasks, whereas IPA incorporates machine learning and cognitive technology to automate and optimize more complex processes [53].

This assessment requires a multi-disciplinary approach that incorporates technical expertise, business acumen, and strategic thinking. Moreover, as AI technologies evolve and become more capable, the scope for automation is likely to increase, making the continuous re-evaluation of automation opportunities a necessity in the digital transformation journey.

AI Alignment:

Finally, current processes should be assessed for their alignment with potential AI capabilities. For instance, tasks involving large volumes of data or those requiring real-time decision making can particularly benefit from AI. This step requires a good understanding of both the business processes and the possibilities offered by AI [54]. AI alignment is a critical aspect of AI-based digital transformation that warrants careful attention and planning. It involves aligning AI applications and initiatives with the strategic objectives and values of the organization [55]. A successful digital transformation is not merely about implementing advanced technologies but also about leveraging these technologies to achieve business goals and create value [56]. Thus, assessing the alignment of AI initiatives with business strategy is essential to ensure that AI adoption is purposeful and effective.

AI alignment involves several key dimensions that are essential for AI integration within an organization. Strategic alignment is crucial, as AI initiatives need to align with the organization's strategic objectives to effectively contribute to their achievement. For instance, in an organization aiming to enhance customer service, this might involve implementing AI-powered chatbots or customer analytics systems [57]. Equally important is cultural alignment, where AI initiatives should resonate with the organization's culture and values. This aspect emphasizes the importance of considering ethical implications, transparency, and the impact on employees. In an organization that values transparency, this would mean designing AI systems that are interpretable and explainable [58]. Lastly, operational alignment ensures that AI initiatives are in sync with the organization's operational needs and workflows. This involves smoothly integrating AI systems into existing processes and ensuring that the organization possesses the necessary infrastructure and skills to support these systems [59]. Each of these dimensions plays a vital role in the successful adoption and integration of AI within an organization.

Assessing AI alignment is not a one-time activity but needs to be an ongoing process as business strategies, technologies, and market conditions evolve. Furthermore, AI alignment is not solely the responsibility of the IT department but should involve all key stakeholders, including business leaders, employees, and even customers [55]. AI alignment plays a key role in the success of AI-based digital transformation. Organizations should carefully consider and continuously monitor the alignment of AI initiatives with strategic objectives, cultural values, and operational needs. To achieve AI alignment, organizations should clearly define the goals and objectives for AI-based digital transformation, ensuring that they are aligned with the overall strategy of the organization. It is also important to establish ethical guidelines and principles for AI adoption and to develop processes to ensure that ethical considerations are integrated into AI system design and deployment. The organization should foster cross-functional collaboration among business, IT, data, and the ethics teams to ensure alignment across different organizational areas. The organization must continuously monitor and evaluate AI systems' performance, impact, and alignment with the organization's goals, adjusting and making improvements as needed.

By prioritizing AI alignment throughout the digital transformation process, organizations can maximize the value and impact of AI technologies while ensuring ethical, responsible, and successful implementation. Hence, the current status assessment process can be summarized in the following diagram in Figure 5.

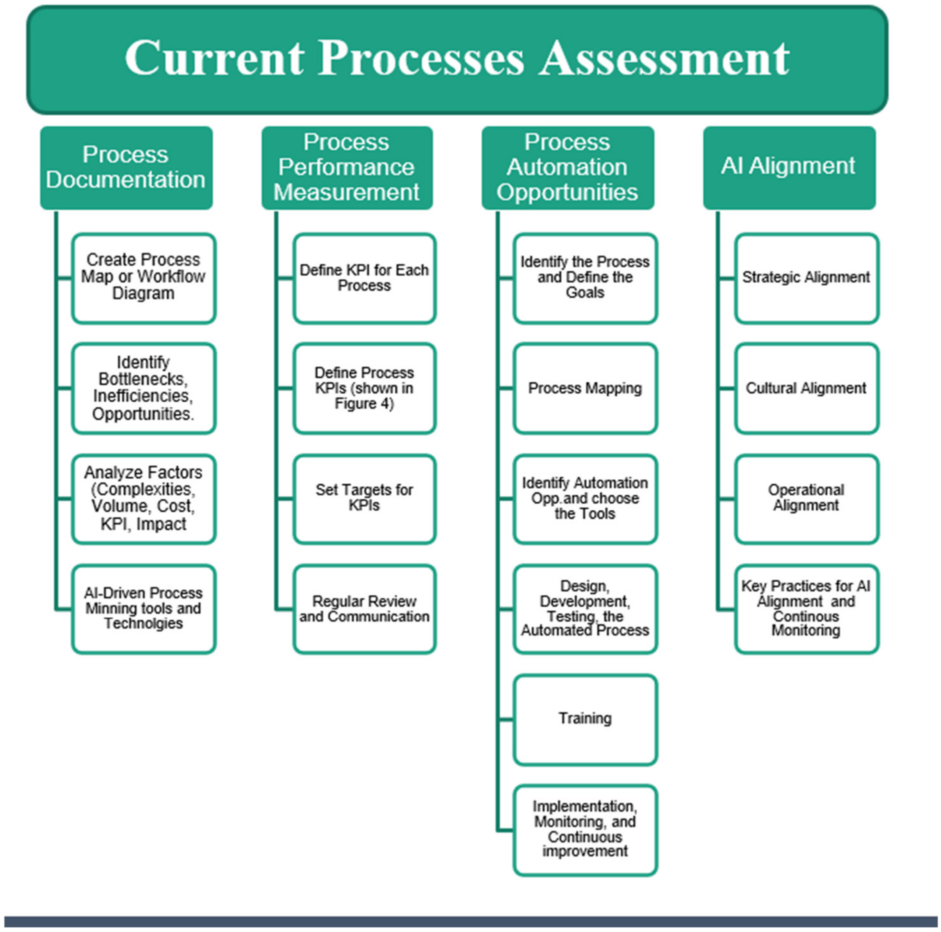

Figure 5. The steps for current processes assessment.

2.2. Existing Systems

Examining the existing technology infrastructure is critical to gauge an organization's technological readiness for AI deployment [60]. This understanding can help identify the required changes in the IT infrastructure and guide the strategic selection of AI tools and technologies. It serves as the foundation for understanding the current technology landscape, which includes hardware, software, data storage, and processing systems. Figure 6 shows the Steps for existing systems assessment.

System Identification:

Identifying the existing systems within an organization is the first step toward AI-based digital transformation. An exhaustive list should include everything from customer relationship management (CRM), and enterprise resource planning (ERP) systems to specialized tools for inventory management, payroll, or content management. It is also crucial to account for informal and legacy systems that are still in use.

Once all systems have been identified, the next step is categorization. Organize the systems and processes into functional categories such as customer management, finance, supply chain, operations, HR, marketing, and sales. Such categorization is pivotal for pinpointing areas where AI can deliver the most impact. Following categorization, evaluate each system's suitability for AI integration. Factors to consider include data availability, system architecture, scalability, flexibility, and compatibility with AI technologies.

An essential part of this process is engaging with users and stakeholders to identify the pain points and inefficiencies. Their insights are valuable for understanding how AI can resolve existing issues and improve the system performance. Concurrently, assessing the technical readiness for AI integration is necessary. This assessment should look at the system architecture, data format compatibility, and integration capabilities with AI frameworks and tools to determine whether system modifications or upgrades are needed.

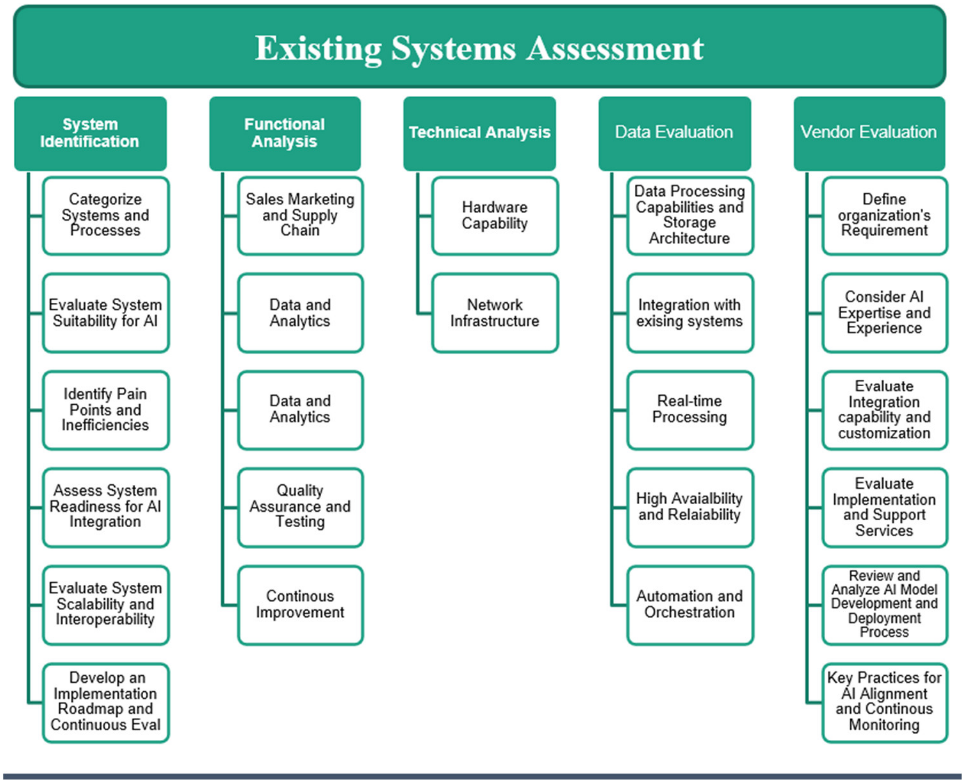

Figure 6. Steps for existing systems assessment.

The scalability and interoperability of the systems must also be evaluated. Check whether the systems can handle increased demands from AI integration and scale accordingly to meet the AI's evolving needs. Assess the ability of systems to communicate and exchange data with one another by checking for existing APIs, connectors, or frameworks that enable this integration.

Finally, develop an implementation roadmap that details the sequence and timeline for AI integration, including the necessary steps, required resources, and milestones. Account for dependencies between systems and prioritize initiatives based on these factors. Remember that system identification is not a one-off task but a continuous part of the AI transformation journey. It is important to constantly evaluate and refine the system identification process, adapting the roadmap based on insights gained from ongoing implementation and feedback.

Functional Analysis:

For each system, conduct a detailed functional analysis. Understand the purpose each system serves, who uses it, what data it handles, and how it interacts with other systems. Document any known issues, limitations, or inefficiencies in the system. This analysis involves evaluating different functional areas within an organization to identify opportunities for AI integration and transformation. In enhancing various functional areas through AI, it is important to consider several key aspects: for customer experience, it is crucial to analyze customer-facing processes and touchpoints, identifying opportunities for AI-driven enhancements such as personalized recommendations, chatbots for customer support, sentiment analysis, and predictive modeling to improve satisfaction and engagement. In the realms of sales, marketing, and supply chain, evaluating processes to determine where AI can boost lead generation, customer segmentation, targeting, and campaign optimization is vital. The role of AI extends to pricing optimization, demand forecasting, customer behavior analysis, and recommendation engines for sales growth. In addition, in supply chain management, AI can streamline operations, enhance forecasting accuracy, optimize inventory management, and improve production planning, with applications in predictive maintenance and operational efficiency monitoring. For data and analytics and strategic decision making, it is essential to evaluate data management and analytics processes to establish a strong AI foundation, focusing on data governance, quality, integration, and infrastructure. The utility of AI in data discovery, cleansing, advanced analytics, and supporting data-driven decision making through predictive analytics, scenario modeling, and intelligent decision support systems is also significant. Lastly, in quality assurance and testing, identifying opportunities for AI integration is key, with applications in automated testing, anomaly detection, and quality control to enhance product or service quality, reduce defects, and boost testing efficiency, thereby facilitating continuous improvement and optimization efforts across all these functional areas.

Technical Analysis:

Performing a technical evaluation of the system is a critical step in understanding an organization's readiness for AI implementation. This evaluation encompasses an examination of the system architecture, compatibility, scalability, security, and performance. It also involves assessing the age of the systems and their ability to support newer technologies, including AI. To gain a comprehensive understanding, this evaluation can be further divided into two main areas: hardware capabilities and the software environment, and network infrastructure and integration capabilities.

In terms of hardware capabilities and the software environment, it is essential to evaluate the computing power and hardware infrastructure available within the organization. This involves assessing whether the existing hardware can meet the computational demands of AI algorithms and models. Factors such as processing speed, memory capacity, and parallel processing capabilities are crucial in this regard. Along with hardware, reviewing the software environment and tools currently used is vital. This review should identify whether the organization possesses the necessary software and development frameworks to support AI initiatives. It is also important to consider whether the organization's software ecosystem is compatible with popular AI platforms, libraries, and frameworks.

Evaluating the network infrastructure is another key aspect. This includes examining the bandwidth capacity and latency to determine whether the organization's network can manage the increased data traffic that AI applications typically bring. Assessing the need for network upgrades or optimizations is crucial to ensure a smooth data transfer and communication between AI systems and data sources. Furthermore, assessing how well the organization's existing technology infrastructure integrates with AI systems and tools is vital. This involves evaluating any limitations or challenges in integrating AI solutions with the organization's current systems, databases, and applications and ensuring compatibility with APIs, data formats, and protocols for seamless data exchange.

Data Evaluation:

Since AI heavily relies on data, take a close look at the type and quality of data that each system handles. Evaluate the data structure, quality, availability, and relevance for potential AI use cases. This can be elaborated by evaluating data processing capabilities and storage architecture. This can be achieved by assessing the processing capabilities of an organization's infrastructure in relation to AI workloads. Consider factors such as the ability to handle large-scale data processing, parallel processing, and distributed computing. Evaluate whether an organization's infrastructure can efficiently handle the computational demands of AI algorithms and models. Evaluate the organization's storage architecture in terms of scalability, performance, and data access. Consider whether the organization has a suitable storage solution, such as distributed file systems or object storage, that can handle the volume, variety, and velocity of data required for AI applications. Assess whether an organization's storage architecture supports efficient data retrieval and processing.

Integration with existing systems should be evaluated. This can be achieved by considering how well an organization's current technology infrastructure integrates with existing systems, applications, and workflows. Assess the compatibility of the organization's infrastructure with legacy systems and third-party applications that may need to interact with AI solutions. Evaluate whether there are any limitations or constraints in integrating AI with the organization's existing technology stack.

The organization should evaluate the real-time processing capabilities. Determine whether the organization's infrastructure supports real-time data processing and analytics. Assess whether the organization has the necessary components, such as stream processing frameworks or event-driven architectures, to enable real-time decision making and AI-driven insights. Consider the ability to handle high-velocity data streams for real-time AI applications. Another important element is high availability and reliability. The organization should evaluate the availability and reliability of its infrastructure. It needs to consider whether the organization has redundant systems, failover mechanisms, or load balancing capabilities to ensure the high availability of AI applications. Assess whether the organization's infrastructure can deliver the required uptime and reliability for critical AI-driven processes.

Finally, the organization should evaluate whether it has the automation and orchestration capabilities to manage AI workflows and processes efficiently. Consider whether the organization has tools or platforms that enable workflow automation, job scheduling, and resource provisioning for AI tasks. Assess whether the organization can streamline the deployment and management of AI models and algorithms.

Vendor Evaluation:

If the systems are provided by external vendors, review the terms of these relationships. Assess the level of vendor support, maintenance, and potential integration with new AI technologies. Tools such as enterprise architecture software (like MEGA, BiZZdesign, or Software AG) can assist in documenting and visualizing the existing system landscape, making it easier to identify gaps, redundancies, and opportunities for improvement [61]. Challenges in this process may include resistance from staff accustomed to legacy systems, uncovering hidden or informal systems, and assessing poorly documented systems. Overcoming these challenges requires a systematic approach, stakeholder involvement, and sometimes expert assistance. Evaluating vendors for AI-based digital transformation is a crucial step to ensure that the organization selects the right partners who can support the organization's goals.

When evaluating vendors for AI-based digital transformation, organizations must systematically and thoroughly approach the process to ensure alignment with their specific needs and long-term objectives. Begin by clearly outlining the organization's requirements and objectives and identifying the specific AI technologies, tools, or the solutions sought, along with the desired outcomes and key performance indicators (KPIs) to achieve. This clarity will guide the assessment of the technological capabilities and offerings of each vendor, examining the breadth and depth of their AI solutions, scalability, performance, compatibility with existing infrastructure, and support for the organization's use cases.

Furthermore, a vendor's AI expertise and experience are critical. Evaluate their proficiency with AI technologies and track record in implementing AI projects, especially those akin to the organization's industry and use cases. Delve into their knowledge of machine learning, data science, and relevant AI frameworks to ensure that they have the depth required for successful delivery.

Integration capabilities are equally important. Assess the vendor's ability to integrate AI solutions with the organization's existing systems, applications, and data sources. This includes their expertise in data integration, API availability, and compatibility with the current technology stack. It is also necessary to consider the vendor's customization abilities and scalability. They should be able to tailor their solutions to the organization's unique requirements and workflows and scale solutions to accommodate the growth and evolving demands of AI initiatives.

Implementation and support services must be scrutinized. Evaluate the vendor's project management approach, training, onboarding programs, and extent of ongoing technical support. Comprehensive documentation, user training, and post-implementation support are crucial for the smooth transition and effective utilization of AI solutions.

The vendor's methodology for AI model development and deployment also demands attention. Consider their practices for model training, validation, deployment, explainability, interpretability, and ethical considerations. The potential for scalability and future growth should not be overlooked; assess the vendor's infrastructure capacity, cloud integration capabilities, and vision for future AI advancements to support the organization's long-term growth.

Vendor support for change management and organizational readiness is a determinant of successful adoption. Evaluate their processes and ability to guide the organization through change management strategies, organizational restructuring, and cultural adaptation. Post-implementation support services, such as technical support, service-level agreements, and timely issue resolution, are also paramount.

Finally, conduct a risk assessment to gauge the potential risks associated with each vendor, including their stability, financial health, data security, and privacy assurances. Compliance with industry regulations and standards, along with proper risk mitigation measures, should be confirmed. The total cost of ownership (TCO) is a decisive factor; hence, consider all costs, such as initial implementation, ongoing maintenance, licensing, and scaling or customization. A comprehensive cost–benefit analysis ensures that the vendor's solutions meet the organization's budget constraints and offer a favorable return on investment (ROI).

2.3. Data Landscape

Data are the lifeblood of AI. Understanding the type of data that are collected, how they are stored and managed, and their use in decision making constitutes a crucial part of the current state assessment [62]. Data quality, governance, privacy, and security are the key considerations in this regard. The assessment of an organization's data landscape is a complex process that encompasses several key facets, as outlined below.

Data Quality:

This involves an assessment of the data's accuracy, integrity, timeliness, completeness, relevancy, and consistency. The poor data quality can lead to incorrect conclusions or faulty machine learning models [63]. Quality issues can arise from various sources, such as data entry errors, missing data, inconsistent data formats, or outdated information. Tools such as IBM's InfoSphere Information Analyzer [64], Informatica Data Quality [65], and Talend Data Quality [66] can help assess and improve data quality.

Data quality is a critical factor in the success of AI-based digital transformation initiatives. Here, are some key considerations for ensuring the data quality in AI-based digital transformation. First, establish robust data governance practices to ensure the data quality throughout its lifecycle. Define data ownership, responsibilities, and processes for data collection, storage, cleaning, and maintenance. Implement the data quality standards, data validation rules, and data access controls. Implement data cleaning and preprocessing techniques to address data quality issues. This may involve removing duplicate records, handling missing values, standardizing data formats, and correcting inconsistencies. Use data cleansing tools and algorithms to automate these processes where possible. **Then,** evaluate the context and relevance of data for AI applications. Ensure that the data used for training AI models are representative, unbiased, and relevant to the desired outcomes. Consider factors such as data source credibility, data sampling techniques, and the representativeness of data for the target population or problem domain. Define data quality metrics that align with the organization's specific AI use cases and objectives. Establish key performance indicators (KPIs) to measure the data quality, such as accuracy, completeness, timeliness, consistency, and relevancy. Regularly monitor these metrics and establish thresholds for acceptable data quality. **Finally**, establish data monitoring and validation processes to continuously assess the data quality. Implement the data quality monitoring tools and techniques to identify anomalies, errors, and data inconsistencies. Regularly validate the data against predefined quality metrics and perform data audits to maintain high-quality data.

Data Accessibility:

It is not enough to have good-quality data; it must also be accessible to those who need it. This includes evaluating the existing data architecture, understanding where the data reside (on-premises or in the cloud), how these are stored (in databases, data warehouses, or data lakes), and how these can be accessed (APIs, SQL queries, etc.) [67]. Data accessibility is a critical aspect of AI-based digital transformation as it enables organizations to effectively leverage their data assets for AI initiatives. To ensure data accessibility, conduct a comprehensive inventory of the organization's data assets; identify the types of data available, their sources, formats, and locations; and document the metadata, such as data definitions, data owners, and data access permissions. In addition, organizations should establish data accessibility governance processes to ensure compliance and adherence to data policies and regulations. Define data accessibility guidelines, data access approval processes, and data usage policies. Regularly monitor data access patterns, review access privileges, and update data accessibility policies as needed. It is vital to maintain the comprehensive documentation of data assets, including their source, transformation processes, and usage history. Document data lineage to track the origin and transformations applied to data. This documentation ensures transparency and enables users to understand the data's context and reliability. Finally, ensure that data accessibility platforms and infrastructure can handle the performance and scalability requirements of AI-based digital transformation. Evaluate system performance, response times, and scalability under different data access scenarios. Scale resources as needed to accommodate increasing data accessibility demands.

Data Governance:

Data governance involves the management of the availability, usability, integrity, and security of the data. It encompasses the data policies, procedures, standards, roles, and responsibilities related to data management, data privacy, and compliance issues [68]. Tools such as Collibra [69] and Informatica Axon [70] can support data governance efforts. Data governance is crucial for AI-based digital transformation initiatives to ensure the availability, integrity, and privacy of data.

Implementing data governance in AI-based digital transformation requires a multifaceted approach to managing data throughout its lifecycle. Begin by establishing a robust data governance framework that details policies, processes, roles, and responsibilities. This framework should articulate data governance objectives, delineate data stewardship roles, and establish cross-functional data governance committees tasked with overseeing data-related activities. Clarity in data ownership and accountability is key to assigning specific individuals or teams within the organization the responsibility for data management.

Data stewards play a pivotal role in ensuring data quality, integrity, and compliance. To foster a culture of accountability for data management, it is important to encourage the organization-wide recognition of the value and importance of data.

To maintain and improve the governance process, regular audits and reviews are essential. These evaluations should assess compliance with established data governance practices, determine their effectiveness, and identify areas that require improvement. Data governance assessments highlight adherence to policies and reveal gaps or non-compliance areas. The insights from these audits should inform the refinement of data governance processes and be applied to AI models and algorithms. Establish guidelines for AI model development, training data selection, model validation, and ongoing monitoring to ensure that ethical considerations and interpretability requirements are met while maintaining transparency and thorough documentation throughout the process.

Metrics and reporting mechanisms play critical roles in data governance. It is important to define specific metrics that can measure the effectiveness of data governance initiatives. Establishing key performance indicators (KPIs) will help track data quality, compliance, accessibility, and the maturity of the data governance process. Develop a regular reporting framework to ensure the clear visibility of governance activities and their progress towards the set objectives.

Recognize that implementing data governance is a change management initiative. It requires clear communication of its importance to all stakeholders, along with fostering a data-driven culture throughout the organization. Providing training and support to employees ensures that they understand and commit to data governance practices. It is also important to address any resistance to change by continuously communicating the benefits and positive impacts of a strong data governance strategy.

Data Volume and Variety:

The amount and types of data collected by the organization can influence the types of AI techniques that can be applied. Large volumes of data can support more complex models such as deep learning. The burgeoning volume of data presents several challenges that are critical to the successful implementation and functioning of AI systems, particularly in the realm of deep learning. The first challenge is the data deluge itself. With exponential data growth being a primary catalyst for AI, especially in deep learning, the resulting vast amounts of data necessitate robust solutions for storage, processing, and management. This 'data deluge' can quickly overwhelm existing infrastructures.

Regarding storage, the sheer scale of data generated today demands more sophisticated and efficient storage solutions. Traditional storage architectures often fail to meet the scalability, performance, and cost-efficiency requirements of intensive AI workloads. Innovations such as non-volatile memory (NVM) and distributed storage systems are being investigated as potential solutions to these storage challenges.

On the processing front, AI models and deep learning algorithms require substantial computational resources to process large datasets. This necessity has prompted an increased reliance on specialized hardware such as GPUs and TPUs, which are designed to accelerate AI training and inference. Alongside hardware solutions, there is a push towards developing new techniques such as model compression, cleaning, and quantization to make AI processing more efficient.

Effective data management becomes crucial when dealing with voluminous data. It is essential for AI systems to implement robust strategies for data cleaning, preprocessing, labeling, and organizing. To simplify the labor-intensive process of data labeling, innovative approaches such as active learning, weak supervision, and transfer learning are being considered.

Another challenge is data heterogeneity, where large datasets often comprise data from myriad sources, each potentially differing in format and structure, complicating integration and reconciliation efforts.

Privacy and security concerns escalate with increasing data volume. More data heighten the risk of breaches and exposure, particularly to sensitive information. As data quantities grow, addressing these privacy and security issues becomes increasingly paramount.

Furthermore, the presence of massive datasets does not inherently resolve the issues of bias and representativeness. Large data volumes can still harbor demographic, cultural, or other biases, potentially skewing AI model accuracy.

Lastly, data access can be a significant hurdle. Organizations might have voluminous datasets at their disposal but are impeded from leveraging them due to legal or regulatory constraints. Ensuring appropriate permissions and licenses for data access and utilization is a non-trivial aspect that organizations must carefully navigate.

Moreover, the variety of data—structured (like databases), semi-structured (like XML files), and unstructured (like text or images)—can also affect the choice of AI models and preprocessing techniques [71].

In the context of AI-based digital transformation, the volume and variety of data are crucial elements that organizations must address. A scalable infrastructure is fundamental for handling the volume and variety of data required for AI initiatives. Organizations should consider cloud-based solutions for flexibility and scalability, which are advantageous when adapting to growing data needs. The deployment of technologies such as distributed storage systems and parallel processing frameworks is also critical to efficiently manage large data volumes.

An organization's data storage and management capabilities must be evaluated to ensure that they can cope with the increased volume and variety of data. It is necessary to implement data management systems that can handle a range of data types, including structured, unstructured, and semi-structured data. Centralized storage solutions, such as data lakes or data warehouses, can be beneficial for efficient data retrieval and storage.

To process and analyze these data, big data processing frameworks and analytics tools are indispensable. Technologies such as Apache Hadoop and Apache Spark, among other distributed computing platforms, enable the parallel processing and analysis of large datasets. Furthermore, leveraging machine learning and AI algorithms can extract valuable insights from varied data sources.

Given the volume and diversity of data, automating data preparation processes is essential. Data preparation tools and technologies can streamline the ingestion, cleansing, and transformation of data. Automated data pipelines and workflows can significantly reduce manual efforts and ensure consistency in data preparation. Lastly, it is crucial to continuously monitor the volume and variety of data to ensure that the organization's infrastructure and processes remain capable of meeting evolving requirements. Implementing monitoring mechanisms to detect shifts in data volume, variety, or data source patterns is necessary. Organizations must regularly assess and adapt their data management strategies to accommodate changes in data characteristics, ensuring ongoing alignment with the organization's AI objectives.

To effectively implement data governance in AI-based digital transformation, organizations must deeply understand the various elements of the data landscape. This understanding is crucial for assessing data readiness for AI, identifying gaps, and devising a strategy to address them. The use of data is a critical facet of this transformation, and several considerations are key to effectively using data in AI initiatives. Organizations should start by defining clear objectives for data usage in AI transformations and determining how data will contribute to specific business goals, process improvements, or innovations. Aligning data usage with strategic objectives ensures a focused and relevant application [72]. A data-driven decision-making culture within an organization is vital. Encouraging stakeholders to base their decisions on data and insights from AI models fosters trust in data and AI processes [73]. Identifying relevant data sources is also essential. An organization must assess both internal and external data sources, including structured and unstructured data, to ensure that they effectively contribute to AI outcomes [74].

Feature engineering is critical for transforming raw data into meaningful features that enhance the performance of the AI model. This involves applying domain knowledge and data analytics techniques to select and transform the most informative attributes [75]. Ethical considerations in data usage cannot be overstated. Organizations must adhere to privacy regulations and data protection policies, employing techniques such as anonymization and encryption to maintain data privacy throughout the AI lifecycle [76].

Measuring ROI and value from data usage in AI initiatives is necessary. This involves establishing KPIs that reflect the organization's goals and tracking the impact of data-driven initiatives [77]. Predictive and prescriptive analytics are powerful tools for leveraging data. Using historical and real-time data, organizations can forecast future trends and behaviors and generate recommendations for optimizing business processes [78]. Personalization enhances customer experience. By leveraging customer data, AI models can create personalized recommendations, targeted marketing, and customized offerings [79]. Data also plays a role in risk management and fraud detection. AI models can be used to identify potential risks or fraudulent patterns, with real-time monitoring systems in place to proactively address these issues [80]. Lastly, continuous improvement and learning from data are imperative. Organizations should establish feedback mechanisms to continuously refine AI models and strategies, allowing for learning and adaptation to new data and business requirements [81]. The data landscape assessment process can be summarized as shown diagram in Figure 7.

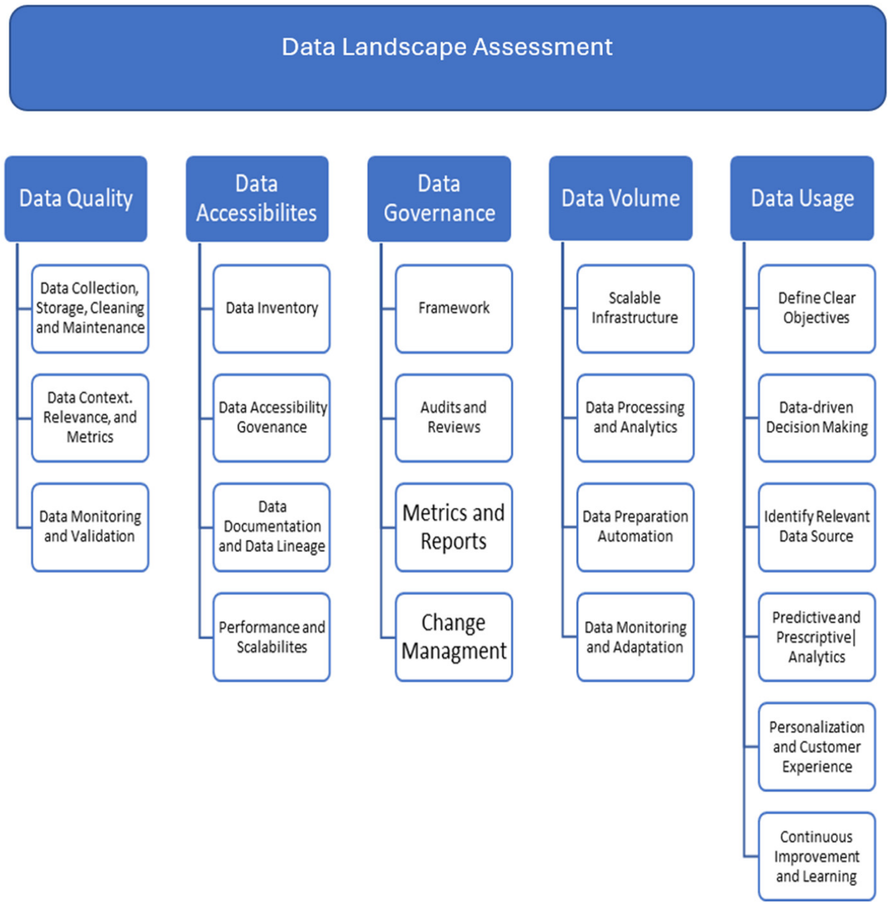

Figure 7. Steps for data landscape assessment.

2.4. AI Capabilities

An organization's AI capabilities, including the existing AI or machine learning initiatives, skills, tools, and infrastructure, need to be evaluated [26]. This step can provide insights into the organization's capacity to embark on AI-based digital transformation. This assessment is multifaceted and encompasses the following key components:

Existing AI Initiatives:

Understanding the existing AI or machine learning projects in an organization provides critical insights into the organization's experience with AI technologies and highlights recurring issues or challenges faced during these initiatives. Analyzing the scope, outcomes, and lessons learned from past and ongoing AI projects is invaluable for identifying potential pitfalls and adopting best practices in future projects [53].

When assessing existing AI initiatives in the context of digital transformation, it is important to evaluate the objectives of each project. Understanding the intended outcomes, such as improving operational efficiency, enhancing customer experience, or driving innovation, and aligning them with the overall AI strategy is crucial for assessing their relevance to the organization's digital transformation goals [82].

In the realm of data use and model development, it is essential to analyze how data are being used in current AI initiatives. Assessing the types of data, their quality, volume, and variety, and evaluating the effectiveness of data preprocessing, feature engineering, and data integration techniques used in these projects is crucial. In addition, reviewing the development process of AI models within these initiatives is key. This review should include an assessment of the algorithms, techniques, frameworks used, level of automation, model selection, and hyperparameter tuning techniques employed. Evaluating the model performance, accuracy, and generalization capability, as well as the integration of AI models with existing systems or processes, is also important. This includes considering the scalability, reliability, and availability of the deployed models, their level of integration with other IT systems, such as CRM, ERP, or IoT platforms, and the efficiency of model monitoring and feedback loops for continuous improvement.

Evaluating the impact and value generated by existing AI initiatives is another critical step. This involves assessing measurable outcomes, such as cost savings, revenue growth, or improved customer satisfaction, and analyzing the effectiveness of AI solutions in achieving the desired objectives and driving business value. Feedback from stakeholders and end-users regarding the perceived benefits and limitations of the initiatives should also be considered [83].

Finally, analyzing mechanisms for the continuous improvement and learning from existing AI initiatives is essential. This includes evaluating feedback loops, monitoring processes, adaptation strategies, and using user feedback, data-driven insights, and emerging technologies to refine and enhance existing AI solutions. The organizational impact of AI initiatives should be assessed, including the level of change management required to integrate AI solutions into existing processes, workflows, or organizational structures, considering the cultural shift, skill development, and organizational readiness for embracing AI-driven changes. Identifying challenges related to change management and planning for mitigating resistance or barriers is also an important aspect of this assessment [84,85].

Skills and Expertise:

Assessing the technical skills and expertise within an organization is a fundamental aspect of preparing for AI-based digital transformation. This involves identifying staff members who possess skills in data science, machine learning, or related fields and pinpointing gaps in expertise that might require filling through recruitment, training, or external partnerships. This assessment is crucial for the effective planning and execution of AI initiatives because a lack of necessary skills can significantly hinder the success of these projects [86].

The first step is to identify the specific technical skills required for AI-based digital transformation initiatives. This includes skills in programing languages such as Python or R, understanding machine learning algorithms, statistical analysis, data manipulation, and data visualization [87,88]. A comprehensive list of relevant skills that align with the organization's AI strategy should be created. Conducting an inventory of the current skills and expertise of the organization's employees is essential to assess their proficiency in the identified technical areas and their experience in AI-related projects. This assessment can be conducted through various methods such as self-assessments, surveys, interviews, or performance evaluations.

The next step involves conducting a skill gap analysis. This entails comparing the current skills inventory with the skills required for AI initiatives. Identifying these skill gaps is crucial to understanding where an organization's capabilities fall short of its AI objectives [89]. Based on this analysis, developing training and upskilling programs is necessary to enhance the technical skills of employees. These could include workshops, online courses, or specialized training programs in areas relevant to AI, machine learning, and data science [90].

The third step is to evaluate the need for external expertise. If certain skills are lacking internally, it might be necessary to hire data scientists, AI specialists, or consultants who specialize in AI and data science. Collaborating with external partners, research institutions, or industry experts can provide access to additional technical skills and knowledge [91].

Finally, creating career development paths and growth opportunities for employees interested in AI and data science is essential. Providing mentorship programs, job rotations, or project assignments allows employees to apply and enhance their technical skills in AI initiatives. Supporting employees in gaining certifications or pursuing advanced degrees in relevant fields is also beneficial. Evaluating employees' practical experience with AI technologies and tools, including their involvement in AI projects such as data preprocessing, model development, and deployment, is also important. Identifying individuals with hands-on experience in implementing AI solutions and working with real-world datasets is key to building a robust AI-capable workforce [92].

Tools and Infrastructure:

Evaluating the current AI infrastructure is critical in determining whether an organization has the necessary hardware and software to support AI projects. This includes assessing data storage capacity, computing power, and networking capabilities. Understanding the available and suitable AI tools and platforms, such as cloud-based AI services and AI development tools, is also essential for effective strategic planning [93]. For AI-based digital transformation, having the right tools and infrastructure is crucial.

In terms of data preprocessing and cleaning, tools such as pandas, scikit-learn, and Apache Spark are popular choices. These assist in handling missing data, outlier detection, data normalization, and feature scaling [94,95]. For machine learning and AI development, selecting appropriate tools and frameworks is vital. Python libraries such as TensorFlow, PyTorch, and scikit-learn offer a range of algorithms, models, and development frameworks for building, training, and deploying AI models [96].

For model training, deployment, and serving, tools that facilitate these processes, such as hyperparameter tuning, model evaluation, and comparison, are essential. Google Cloud AutoML, H2O.ai, or Microsoft Azure Machine Learning Studio are popular options [97–99]. Additionally, tools such as TensorFlow Serving, Amazon SageMaker, and Microsoft Azure ML Deployment help in deploying and serving AI models in production [100–102].

Automated machine learning (AutoML) tools such as Google Cloud AutoML, H2O.ai's Driverless AI, or DataRobot automate the machine learning process from data preprocessing to model selection and tuning, even for those with limited expertise [103–105]. Data visualization and reporting tools such as Tableau, Power BI, or matplotlib/seaborn in Python are crucial for effectively communicating insights and results [106–108].

For textual data, tools for natural language processing and text analytics, such as the Natural Language Toolkit (NLTK), spaCy, or Google Cloud NLP API, are important for tasks such as sentiment analysis or text classification [109–111]. In computer vision and image processing, tools such as OpenCV, TensorFlow's Object Detection API, and Microsoft Azure Computer Vision enable tasks such as object detection or image segmentation [112–114].

Leveraging cloud infrastructure for AI-based digital transformation is essential. Cloud platforms such as AWS, GCP, and Microsoft Azure provide scalable solutions for data storage, model training, and deployment. Edge computing capabilities are also significant for real-time AI applications, with platforms such as NVIDIA Jetson, Intel Movidius, or Google Coral for edge AI deployments [115,116]. DevOps and MLOps practices streamline AI model development, deployment, and maintenance, using tools for version control, continuous integration, and model monitoring such as Git, Jenkins, Docker, or Kubeflow. Explainability and interpretability tools such as SHAP, Lime, and IBM AI Explainability 360 are crucial for understanding AI model decision making and addressing bias and transparency concerns [117,118].

Finally, automated data pipelines are key for efficient data movement from various sources to AI systems. Tools such as Apache Airflow, AWS Glue, and Google Cloud Dataflow are useful for this purpose [119–121]. Model versioning and management tools such as MLflow, DVC, and Git LFS help in tracking and managing different versions of AI models for reproducibility and traceability [122–124].

Culture and Leadership:

The integration of AI within an organization is deeply influenced by its culture and leadership. A supportive leadership team and an organizational culture that values openness, collaboration, and innovation can significantly boost the success rate of AI projects. Conversely, resistance to change, lack of commitment from leadership, and poor collaboration can impede AI adoption [72].

Leadership buy-in and support are indispensable for AI-driven transformation. Leaders must not only advocate for AI but also communicate its significance and commit the necessary resources to its adoption. Their active participation affirms their commitment to AI initiatives [125].

AI-induced transformation is inherently a change management exercise. It is crucial to devise strategies that address employee apprehensions and the potential fear of job displacement. Cultivating an environment that welcomes change and advocates continuous learning is key to successful transformation [126].

Building a learning culture that encourages innovation and continuous improvement is another cornerstone. Providing ongoing training and development opportunities allows employees to enhance their AI competencies. A culture that motivates employees to explore new AI techniques and technologies can be very powerful. Moreover, promoting a culture where decisions are made on the basis of data is essential. Employees should be encouraged to use AI insights to inform their decisions with robust frameworks in place to support this approach at all organizational levels [127].

Investment in continuous leadership development tailored to AI is crucial. Leaders should be equipped with the necessary knowledge and skills to effectively steer and support AI initiatives. They should also have opportunities to keep abreast of the latest AI advancements and industry trends [128].

Finally, it is important to measure and celebrate the successes of AI initiatives. Establishing clear metrics to gauge the impact of AI on the organization and acknowledging the contributions of employees are important. Providing feedback and rewards for individual and team efforts can reinforce positive outcomes and support further AI integration efforts. The AI capability assessment process can be summarized in diagram shown in Figure 8.

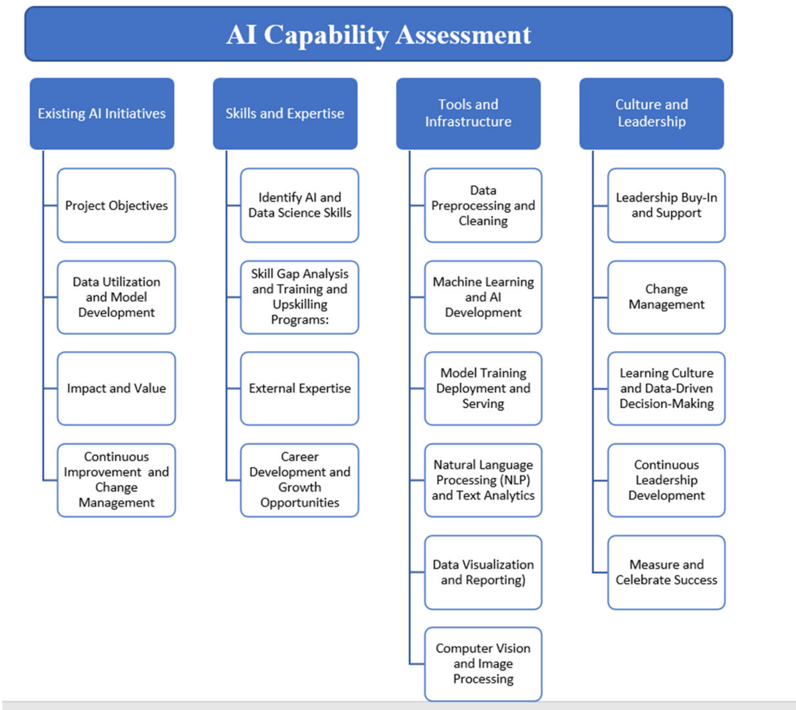

Figure 8. AI capability assessment.

3. Results

Assessing an organization's current status for AI-based digital transformation can be systematically approached through a framework structure. This framework, as shown in Figure 9, evaluates various aspects of the organization's readiness and capabilities across several key dimensions:

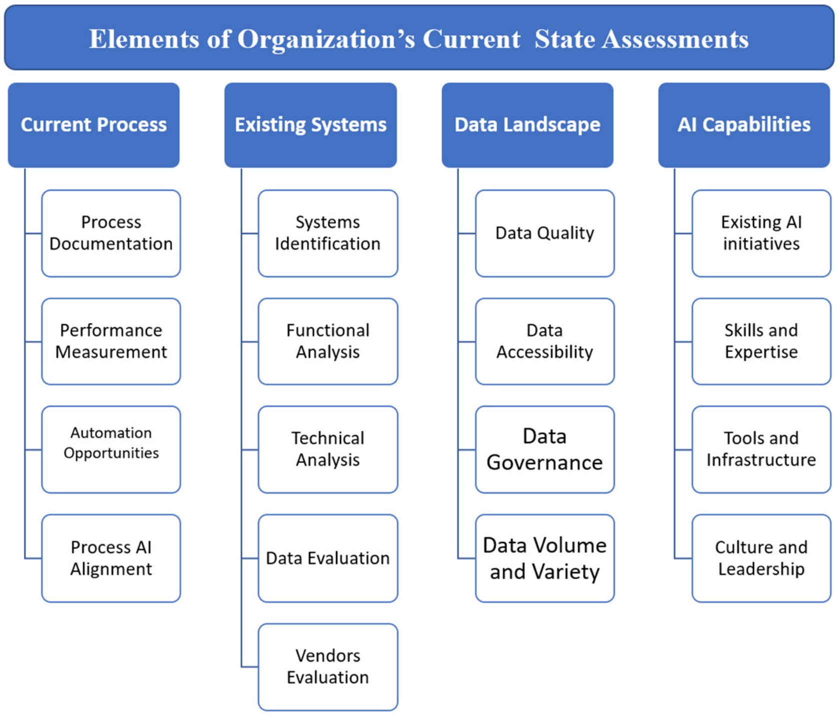

Figure 9. Elements of the current status assessment structure.

The first dimension, current process, focuses on evaluating existing business processes for AI integration. It entails a detailed analysis of the organization's current workflows to identify areas where AI can enhance efficiency. This examination delves into the intricacies of existing processes, uncovering inefficiencies, redundancies, and bottlenecks. Understanding these processes allows organizations to strategically integrate AI, streamlining operations, and improve productivity.

Next, existing systems aim to assess the organization's technology infrastructure and applications. This dimension scrutinizes the technological backbone of the organization, evaluating hardware, software, and the overall IT architecture. It considers factors such as compatibility, scalability, and integration capabilities. By identifying the strengths and weaknesses in the existing systems, organizations can make informed decisions about the necessary upgrades or modifications for smooth AI integration.

The Data Landscape dimension analyses the quality, quantity, and accessibility of organizational data. It involves a thorough assessment of data sources, data quality, and data management practices. This analysis ensures that the data are reliable, accessible, and diverse enough to meet the requirements of AI algorithms. Understanding the data landscape is crucial for mitigating biases and enhancing the accuracy of AI-driven insights.

AI capabilities is another critical dimension that focuses on evaluating an organization's current AI-related knowledge and skills. It examines the existing talent pool, training programs, and partnerships with external AI experts. This assessment helps identify gaps in skills and knowledge, which are essential for planning targeted training programs and strategic collaborations. It ensures that the organization is equipped to effectively leverage AI technologies.

By employing this structured evaluation framework, organizations can gain a comprehensive understanding of their readiness for AI integration. The insights from each dimension enable organizations to identify skill gaps, make strategic decisions about training and external expertise, and foster a culture of continuous learning. This thorough assessment forms a solid foundation for a successful and adaptive AI-based digital transformation journey.

4. Discussion

Assessing an organization's current state is a critical step in AI-based digital transformation. It provides valuable insights into the organization's strengths, weaknesses, and readiness to adopt AI technologies. Through this assessment, organizations can identify gaps, develop a strategic roadmap, and effectively allocate resources [24]. By understanding the technological infrastructure, data availability, organizational culture, talent pool, business processes, and regulatory considerations, organizations can make informed decisions and embark on a successful AI-driven digital transformation journey [26].

The process starts with assessing organizational needs and objectives by understanding the organization's strategic goals, challenges, and areas where AI can bring value. This leads to identifying the specific business processes, decision making, or customer experience aspects that could benefit from AI [27].

The assessment of the current state of an organization for AI-based digital transformation includes the evaluation of the potential for automation within the identified systems through AI [37]. It is based on the analysis of operational data to identify bottlenecks, inefficiencies, or areas for improvement in order to implement AI-driven process automation to streamline operations, reduce costs, and enhance productivity. This identification process may require you to engage system users and stakeholders. This involvement seeks their input and feedback on the systems' strengths, weaknesses, and areas for improvement by understanding their requirements and expectations to ensure that AI integration aligns with their needs. In addition, assessing the involvement and engagement includes an evaluation of the collaboration and communication processes within the organization to identify opportunities for AI-driven enhancements in applications for natural language processing, virtual assistants, and knowledge management systems to facilitate efficient collaboration and communication.

AI is a technology that heavily depends on data, which must be of high quality, in proper format, available, and accessible [63]. Therefore, it is essential to assess data quality, availability, and accessibility within each system. It is important to identify the data required for AI initiatives and assess whether they are captured, stored, and structured effectively. This must cover the consideration of data gaps, inconsistencies, and data integration challenges that need to be addressed for AI implementation. Therefore, it is essential to determine the data sources feeding into each system and the flow of data between systems [74]. This naturally leads to the identification of the critical data points and processes that contribute to the functioning of the systems, such as any data gaps or bottlenecks that need to be addressed to ensure comprehensive AI implementation. The assessment of the current state covers the capability of the organization to handle a huge growing amount of data. This requires the assessment of data compression and storage optimization within the organization. Advanced capability to implement data compression techniques to reduce the storage requirements for large volumes of data. Use compression algorithms such as gzip, zlib, or Snappy to compress data files without sacrificing data integrity. In addition, explore storage optimization techniques, such as data deduplication or data archival strategies, to efficiently manage and store large volumes of data. This may include data lake architecture that allows the storage of diverse data types in their raw form to provide a centralized repository for storing structured and unstructured data, enabling easy access for AI-based analysis and processing [67]. Leverage data lake architectures to support the variety and scalability of data. This allows data handling to be taken to a further step related to data integration and data fusion from multiple sources to create a comprehensive and holistic view to combine data from disparate systems or departments to gain insights that may not be apparent when analyzing individual data sources in isolation as a result of data integration techniques to ensure seamless data connectivity and interoperability. There are tools that facilitate data integration and extract, transform, load (ETL) processes [129]. These tools enable the seamless extraction of data from various sources, transformation into a usable format, and loading into the target systems. The organization may consider tools such as Apache Kafka [130], Talend [131], or Informatica [132] for efficient data integration. Implement alerts or triggers to notify stakeholders of any significant changes or deviations in data patterns. Humans cannot deal with data in any format by requiring data exploration and visualization techniques to gain insights from the data by using exploratory data analysis (EDA) [133] to understand the characteristics, patterns, and relationships within the data. It is practical and time saving to visualize data through interactive dashboards, charts, and graphs to effectively communicate insights to stakeholders. It provides deep insight into the use of data visualization and storytelling techniques to effectively communicate insights derived from data.

Such a project requires an analysis of the compliance process and risk management activities to identify areas where AI can improve efficiency, accuracy, and risk assessment, and where AI applications for regulatory compliance monitoring, fraud detection, anomaly detection, and automated compliance reporting can be used across different functional areas. The assessment of the current state includes the evaluation of risk assessment and fraud detection processes to identify opportunities for AI applications to automate risk analysis, identify patterns of fraudulent activities, and enhance fraud detection capabilities. Furthermore, it must assess compliance and ethics processes to identify areas where AI can ensure adherence to regulatory requirements and ethical standards. This promotes AI applications for automated compliance monitoring, audit trail analysis, and ethical decision support systems.

Therefore, the other dimension of AI-based digital transformation is related to expertise, knowledge transfer, and upskilling. The adoption of such technology requires promoting knowledge transfer and upskilling initiatives to empower employees with the skills and knowledge to effectively utilize data. Success can be maintained by providing training programs on data analysis, AI techniques, and data visualization tools and by fostering a data-literate workforce that can leverage data insights for informed decision making. This encourages risk taking and innovation in AI initiatives as it creates an environment where employees feel empowered to experiment, learn from failures, and propose new ideas to recognize and reward innovation and creative problem solving. This leads to the development of an agile and adaptive mindset to respond to the rapidly changing AI landscape, to encourage flexibility, agility, and adaptability in AI projects, and to foster an environment that embraces iteration, feedback, and continuous improvement. AI-based digital transformation requires continuous learning and adaptation to recognize that technical skills in AI and data science are continuously evolving. This requires encouraging employees to stay updated with the latest advancements, trends, and technologies in AI through participation in conferences, webinars, or industry events. Foster a culture of continuous learning and adaptation to keep pace with the fast-changing AI landscape. As technology continues to advance and high-level skills are needed, the issue of cross-functional collaboration arises to assess employees' ability to collaborate across different functions and domains to identify individuals who can effectively communicate and work with stakeholders from various backgrounds, such as business teams, domain experts, or data scientists, to bridge the gap between technical expertise and business requirements. To keep up with technological advancements, employees should have updated industry knowledge and awareness. Hence, it is essential to evaluate employees' knowledge of industry-specific AI applications, trends, and challenges to identify individuals who stay updated with the latest developments in AI within the organization's industry, follow industry-specific AI use cases, and understand the unique considerations and opportunities for AI-based digital transformation in the organization's sector. This takes employees to a higher level of continuous integration and deployment (CI/CD) [134] evaluation of their knowledge of CI/CD practices for AI model development and deployment. This indicates that they understand version control, automated testing, and continuous integration processes, which are crucial for maintaining code quality and ensuring the smooth deployment of AI models.

Comprehensively covering AI skills among employees is vital, and this includes a variety of technological proficiencies. The expertise in natural language processing (NLP) techniques is crucial, particularly for organizations that handle textual data. Proficiency in deep learning techniques and neural networks, which form the backbone of many AI applications, should also be assessed among employees. For those dealing with image or video data, skills in computer vision are essential. Additionally, employee proficiency in big data technologies like Apache Hadoop or Apache Spark is important, as these technologies are commonly used for processing large volumes of data. Familiarity with cloud platforms such as Amazon Web Services (AWS), Google Cloud Platform (GCP), and Microsoft Azure should be evaluated, considering their increasing importance in AI and data processing. Knowledge of DevOps practices and ML Ops (machine learning operations) principles is another critical area to assess, as these are increasingly relevant for efficient AI deployment and maintenance. Skills in data engineering, which include data integration, preprocessing, and pipeline development, are essential for managing the data lifecycle. Lastly, proficiency in data visualization tools and techniques should also be evaluated, as this skill is key in effectively communicating insights from data.

However, AI-based digital transformation presents organizations with multifaceted challenges, inherent risks, and potential pitfalls that necessitate comprehensive analysis and strategic mitigation strategies. At the core of these challenges lies the intricate issue of data quality and availability. Organizations frequently encounter deficiencies and biases within datasets, which impede the accuracy and reliability of AI algorithms. In addition, a persistent scarcity of skilled professionals well versed in AI technologies amplifies the challenge, demanding extensive training initiatives and proactive talent acquisition efforts. The integration of AI systems with existing technologies poses a formidable challenge, requiring meticulous planning and implementation to ensure harmonious co-existence and minimal disruptions to ongoing operations.

From a risk perspective, the vulnerability of AI systems to security breaches is a significant concern. Inadequately secured AI frameworks become susceptible targets for cyber-attacks, potentially leading to severe data breaches and the compromise of sensitive information. Furthermore, the ethical risk of algorithmic bias remains pronounced, with biased training data perpetuating societal prejudices and reinforcing discriminatory outcomes. An additional risk materializes in the form of over-reliance on AI technologies without adequate human oversight, particularly in sectors with high-stakes decision-making requirements, such as healthcare or finance, raising concerns about erroneous outcomes and potential ethical dilemmas.

In tandem with these challenges and risks, organizations must navigate the potential pitfalls inherent to AI-based digital transformation. Unrealistic expectations often cloud the transformative potential of AI technologies, leading to disillusionment if capabilities are overestimated or inadequately understood. Vendor lock-in, in which organizations excessively rely on specific AI vendor ecosystems, can stifle flexibility and hinder innovation. Inadequate pre-deployment testing poses a significant pitfall because insufficiently tested AI applications are prone to unexpected failures, causing disruptions and eroding stakeholder trust. Lastly, the absence of continuous monitoring and adaptation strategies renders AI solutions susceptible to obsolescence, inefficiency, or ethical quandaries over time.

Effectively addressing these challenges and mitigating associated risks and pitfalls necessitates a nuanced, adaptable approach grounded in rigorous academic inquiry. Organizations must prioritize the cultivation of high-quality, unbiased datasets, invest in continuous education and training initiatives, and implement robust cybersecurity protocols. Moreover, fostering a culture of innovation and ethical awareness is imperative to encourage interdisciplinary collaboration, knowledge dissemination, and ongoing discourse within the academic and professional community. Through these concerted efforts, organizations can navigate the complexities of AI-based digital transformation in an academically rigorous and ethically sound manner, thereby realizing the transformative potential while minimizing associated risks.

To accommodate the future growth of the organization and greater usage and dependency on AI-based digital transformation, the organization has to assess the current state of the scalability and flexibility of existing AI initiatives to accommodate future growth and evolving business needs and assess the ability of AI solutions to handle increasing data volumes, user demands, or changing market dynamics. The organization may consider the extensibility and adaptability of the AI infrastructure, models, and algorithms to support scalability and flexibility.

5. Conclusions

This research systematically explored and elucidated the key assessment elements crucial for the successful integration of AI technologies within organizational contexts. This study has contributed a comprehensive framework designed to guide organizations in their AI-based digital transformation endeavors. These elements not only draw from established theories but also emphasize their real-world impact. By meticulously conducting these assessments, organizations can gain profound insights into their existing strengths and areas that need improvement. Acknowledging the limitations inherent in any research, such as contextual variations and the rapidly evolving nature of AI technologies, our work provides a solid foundation for future academic inquiry and practical applications. As the landscape of AI-based technologies continues to evolve, our research points toward essential areas for further investigation. Future studies might explore specific industry applications, the impact of cultural and regulatory factors, and the development of adaptive frameworks capable of accommodating dynamic organizational needs. In the realm of practical applications, organizations are encouraged to embrace our guidelines as a starting point for their AI-based digital transformation initiatives. We emphasize the paramount importance of feedback mechanisms and continuous improvement strategies. By fostering a culture of iterative learning and adaptation, organizations can ensure the sustained relevance and effectiveness of their AI integration efforts. In the academic sphere, scholars are encouraged to delve deeper into the nuanced intersections of AI technology and organizational dynamics.

It is important to mention that this research underscores the importance role of AI technologies in shaping the future of organizations. Through our comprehensive framework, we have illuminated the pathway for integrating AI within the organizational fabric, balancing both academic rigor and the practical exigencies of technological implementation. However, we acknowledge that integrating experiential insights, although valuable for capturing real-world complexities, introduces a subjective dimension to our research. This subjective lens is a limitation of the current study and indicates the qualitative nature of experience-driven research. Moreover, while our findings provide actionable guidelines, they are by their very nature influenced by the specific contexts from which our experiences arise. This underscores the necessity for future research to validate and extend these findings across diverse contexts and to critically assess the transferability of our framework to different organizational environments.

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References

1. Gołąb-Andrzejak, E. AI-powered Digital Transformation: Tools, Benefits and Challenges for Marketers–Case Study of LPP. *Procedia Comput. Sci.* **2023**, *219*, 397–404. [CrossRef]
2. Kim, K.; Kim, B. Decision-making model for reinforcing digital transformation strategies based on artificial intelligence technology. *Information* **2022**, *13*, 253. [CrossRef]
3. Gill, S.S.; Xu, M.; Ottaviani, C.; Patros, P.; Bahsoon, R.; Shaghaghi, A.; Golec, M.; Stankovski, V.; Wu, H.; Abraham, A.; et al. AI for next generation computing: Emerging trends and future directions. *Internet Things* **2022**, *19*, 100514. [CrossRef]
4. Bogers, M.L.A.M.; Garud, R.; Thomas, L.D.W.; Tuertscher, P.; Yoo, Y. Digital innovation: Transforming research and practice. *Innovation* **2022**, *24*, 4–12. [CrossRef]
5. Ancillai, C.; Sabatini, A.; Gatti, M.; Perna, A. Digital technology and business model innovation: A systematic literature review and future research agenda. *Technol. Forecast. Soc. Change* **2023**, *188*, 122307. [CrossRef]
6. Jarrahi, M.H.; Kenyon, S.; Brown, A.; Donahue, C.; Wicher, C. Artificial intelligence: A strategy to harness its power through organizational learning. *J. Bus. Strategy* **2023**, *44*, 126–135. [CrossRef]
7. Rožman, M.; Oreški, D.; Tominc, P. Artificial Intelligence-Supported Reduction of Employees' Workload to Increase the Company's Performance in Today's VUCA Environment. *Sustainability* **2023**, *15*, 5019. [CrossRef]
8. Raffey, M.A.; Gaikwad, S.B. The Impact of Artificial Intelligence on Business Operations: Investigating The Current State And Future Implications Of AI Technologies. *J. Pharm. Negat. Results* **2022**, 5577–5580. [CrossRef]
9. Mihai, F.; Aleca, O.E.; Gheorghe, M. Digital Transformation Based on AI Technologies in European Union Organizations. *Electronics* **2023**, *12*, 2386. [CrossRef]
10. Khanom, M.T. Business Strategies in The Age of Digital Transformation. *J. Bus.* **2023**, *8*, 28–35.
11. Perifanis, N.-A.; Kitsios, F. Investigating the influence of artificial intelligence on business value in the digital era of strategy: A literature review. *Information* **2023**, *14*, 85. [CrossRef]
12. Fan, Q.; Ouppara, N. Surviving disruption and uncertainty through digital transformation: A case study on small to medium-sized enterprises (SME). In *Moving Businesses Online and Embracing E-Commerce: Impact and Opportunities Caused by COVID-19*; IGI Global: Beijing, China, 2022; pp. 1–22.
13. Şişci, M.; Torkul, Y.E.; Selvi, I.H. Machine Learning as a Tool for Achieving Digital Transformation. *Knowl. Manag. Digit. Transform. Power* **2022**, *1*, 55.
14. O'Callaghan, M. *Decision Intelligence: Human—Machine Integration for Decision-Making*; CRC Press: Boca Raton, FL, USA, 2023.
15. King, K. *Using Artificial Intelligence in Marketing: How to Harness AI and Maintain the Competitive Edge*; Kogan Page Publishers: London, UK, 2019.
16. Brunetti, F.; Matt, D.T.; Bonfanti, A.; De Longhi, A.; Pedrini, G.; Orzes, G. Digital transformation challenges: Strategies emerging from a multi-stakeholder approach. *TQM J.* **2020**, *32*, 697–724. [CrossRef]
17. Brock, J.K.U.; Von Wangenheim, F. Demystifying AI: What digital transformation leaders can teach you about realistic artificial intelligence. *Calif. Manag. Rev.* **2019**, *16*, 110–134. [CrossRef]
18. Jan, J.; Weißert, M.; Wyrtki, K. Ready or not, AI comes—An interview study of organizational AI readiness factors. *Bus. Inf. Syst. Eng.* **2021**, *63*, 5–20.
19. Davenport, T.H. *The AI advantage: How to Put the Artificial Intelligence Revolution to Work*; MIT Press: Cambridge, MA, USA, 2018.
20. Kitsios, F.; Kamariotou, M. Artificial intelligence and business strategy toward digital transformation: A research agenda. *Sustainability* **2021**, *13*, 2025. [CrossRef]
21. Vidu, C.-M.; Pinzaru, F.; Mitan, A. What managers of SMEs in the CEE region should know about challenges of artificial intelligence's adoption?—An introductive discussion Co menedżerowie MŚP w regionie Europy Środkowo-Wschodniej powinni wiedzieć o wyzwaniach związanych z wprowadzeniem. *Nowocz. Syst. Zarządzania* **2022**, *17*, 63–76. [CrossRef]
22. Cayirtepe, Z.; Senel, F.C. The future of quality and accreditation surveys: Digital transformation and artificial intelligence. *Int. J. Qual. Health Care* **2022**, *34*, mzac025. [CrossRef]
23. Ross, J.W.; Beath, C.M.; Mocker, M. Designing a digital organization. *MIT Sloan Manag. Rev.* **2018**, *59*, 57–65.
24. Smith, D.R. Creation of a Unified Cloud Readiness Assessment Model to Improve Digital Transformation Strategy. *Int. J. Data Sci. Anal.* **2022**, *8*, 11. [CrossRef]
25. Ahlberg, J.; Eriksson, C. *To Measure Organizational Wellness with AI-A Future Competitive Advantage?* Department of Business Administration, Lund University Press: Lund, UK, 2021.
26. Davenport, T.; Guha, A.; Grewal, D.; Bressgott, T. How artificial intelligence will change the future of marketing. *J. Acad. Mark. Sci.* **2020**, *48*, 24–42. [CrossRef]
27. Bughin, J.; Chui, M.; Manyika, J. *Artificial Intelligence: The Next Digital Frontier?* McKinsey Global Institute: New York, NY, USA, 2018.
28. Scheer, A.W. *Architecture of Integrated Information Systems: Foundations of Enterprise Modeling*; Springer: Berlin/Heidelberg, Germany, 2018.
29. Jaheer Mukthar, K.P.; Sivasubramanian, K.; Asis, E.H.R.; Guerra-Munoz, M.E. Redesigning and Reinvention of Retail Industry Through Artificial Intelligence (AI). In *Future of Organizations and Work After the 4th Industrial Revolution: The Role of Artificial Intelligence, Big Data, Automation, and Robotics*; Springer International Publishing: Cham, Switzerland, 2022; pp. 41–56.

30. Melville, N.; Kraemer, K.; Gurbaxani, V. Review: Information technology and organizational performance: An integrative model of IT business value. *MIS Q.* **2018**, *28*, 283–322. [CrossRef]
31. Jeston, J. *Business Process Management: Practical Guidelines to Successful Implementations*; Routledge: London, UK, 2018.
32. Van Der Aalst, W.M.; Bichler, M.; Heinzl, A. *Data-Driven Process Discovery and Analysis*; Springer Nature: Berlin/Heidelberg, Germany, 2020.
33. Wamba-Taguimdje, S.-L.; Wamba, S.F.; Kamdjoug, J.R.K.; Wanko, C.E.T. Influence of artificial intelligence (AI) on firm performance: The business value of AI-based transformation projects. *Bus. Process Manag. J.* **2020**, *26*, 1893–1924. [CrossRef]
34. Bisbe, J.; Malagueño, R. How to design a successful KPI system. *MIT Sloan Manag. Rev.* **2018**, *59*, 45–51.
35. Parmenter, D. *Key Performance Indicators: Developing, Implementing, and Using Winning KPIs*, 4th ed.; John Wiley & Sons: Hoboken, NJ, USA, 2015.
36. Bititci, U.S.; Carrie, A.S.; McDevitt, L.; Turner, T. Creating and managing value in collaborative networks. *Int. J. Oper. Prod. Manag.* **2017**, *37*, 87–102. [CrossRef]
37. Lacity, M.; Willcocks, L. Nine keys to unlocking digital transformation in business operations. *MIS Q. Exec.* **2016**, *15*, 135–149.
38. Fischer, T. *Robotic Process Automation*; Springer: Wiesbaden, Germany, 2018.
39. Hammer, M.; Stanton, S. *Reengineering the Corporation: A Manifesto for Business Revolution*; Harper Business: New York, NY, USA, 2019.
40. Dumas, M.; La Rosa, M.; Mendling, J.; Reijers, H.A. *Fundamentals of Business Process Management*; Springer: Berlin/Heidelberg, Germany, 2018.
41. Lee, J.; Lapira, E.; Bagheri, B.; Kao, H.A. Recent advances and trends in predictive manufacturing systems in big data environment. *Manuf. Lett.* **2017**, *11*, 113–120. [CrossRef]
42. Ramaswamy, R.; Gou, Y.; Wu, D.J.; Bush, D.; Grover, P. Organizing for digital innovation: The division of innovation labor between upstream and downstream teams. *J. Manag. Inf. Syst.* **2018**, *35*, 169–204.
43. Smith, H.A.; Fingar, P. *Business Process Management: The Third Wave*; Meghan-Kiffer Press: Tampa, FL, USA, 2017.
44. Lacity, M.; Willcocks, L.; Craig, A. Robotic process automation at Telefónica O2. *MIS Q. Exec.* **2018**, *17*, 99–108.
45. Alavi, M.; Leidner, D.E. Knowledge management and knowledge management systems: Conceptual foundations and research issues. *MIS Q.* **2001**, *25*, 107–136. [CrossRef]
46. Davenport, T.H.; Short, J.E. The new industrial engineering: Information technology and business process redesign. *Sloan Manag. Rev.* **2018**, *29*, 11–27.
47. Power, D.J. *Decision Support Systems: Concepts and Resources for Managers*; Business Expert Press: New York, NY, USA, 2017.
48. Willcocks, L.; Lacity, M.; Craig, A. Robotic Process Automation and Risk Mitigation: The Definitive Guide; SB Publishing, Ashford, UK, 2017.
49. Schwartz, J. Workforce of the future: The competing forces shaping 2030. *Strategy Leadersh* **2019**, *47*, 16–22.
50. Van Der Aalst, W. *Process Mining: Data Science in Action*; Springer: Berlin/Heidelberg, Germany, 2016.
51. Martínez-Rojas, A.; Sánchez-Oliva, J.; López-Carnicer, J.M.; Jiménez-Ramírez, A. Airpa: An architecture to support the execution and maintenance of AI-powered RPA robots. In Proceedings of the International Conference on Business Process Management, Rome, Italy, 10–11 December 2021; Springer International Publishing: Cham, Switzerland, 2021; pp. 38–48.
52. Kholiya, P.S.; Kapoor, A.; Rana, M.; Bhushan, M. Intelligent process automation: The future of digital transformation. In Proceedings of the 2021 10th International Conference on System Modeling & Advancement in Research Trends (SMART), Moradabad, India, 10–11 December 2021; IEEE: New York, NY, USA, 2021; pp. 185–190.
53. Davenport, T.H.; Ronanki, R. Artificial intelligence for the real-world. *Harv. Bus. Rev.* **2018**, *96*, 108–116.
54. Brynjolfsson, E.; McAfee, A. *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*; WW Norton & Company: New York, NY, USA, 2014.
55. Kolbjørnsrud, V. How artificial intelligence will redefine management. *Harv. Bus. Rev.* **2018**, *96*, 62–69.
56. Brynjolfsson, E.; McAfee, A. The business of artificial intelligence. *Harv. Bus. Rev.* **2018**, *96*, 108–116.
57. Nguyen, T.-M.; Malik, A. Cognitive processes, rewards and online knowledge sharing behavior: The moderating effect of organizational innovation. *J. Knowl. Manag.* **2020**, *24*, 1241–1261. [CrossRef]
58. Bryson, J.; Winfield, A. Standardizing ethical design for artificial intelligence and autonomous systems. *Computer* **2017**, *50*, 116–119. [CrossRef]
59. Du, S.; Xie, C. Paradoxes of artificial intelligence in consumer markets: Ethical challenges and opportunities. *J. Bus. Res.* **2021**, *129*, 961–974. [CrossRef]
60. Raguseo, E. Big data technologies: An empirical investigation on their adoption, benefits and risks for companies. *Int. J. Inf. Manag.* **2018**, *38*, 187–195. [CrossRef]
61. Guo, H.; Li, J.; Gao, S.; Smite, D. Boost the potential of EA: Essential practices. In Proceedings of the 23rd International Conference on Enterprise Information Systems, Online, 26–28 April 2021; SciTePress: Setubal, Portugal, 2021.
62. Kiron, D.; Unruh, G. Is Organization's Business Ready for a Digital Future? *MIT Sloan Manag. Rev.* **2018**, *59*, 21–25.
63. Aldoseri, A.; Khalifa; Al-Khalifa, N.; Hamouda, A.M. Re-Thinking Data Strategy and Integration for Artificial Intelligence: Concepts, Opportunities, and Challenges. *Appl. Sci.* **2023**, *13*, 7082. [CrossRef]
64. IBM InfoSphere Information Analyzer. Available online: https://www.ibm.com/products/infosphere-information-analyzer (accessed on 24 September 2023).

65. Informatic Data Quality. Available online: https://www.informatica.com/gb/products/dataquality/informatica-dataquality.html (accessed on 29 September 2023).
66. Talend Data Quality. Available online: https://www.talend.com/products/data-quality/ (accessed on 3 October 2023).
67. Li, R.; Rao, J.; Wan, L. The digital economy, enterprise digital transformation, and enterprise innovation. *Manag. Decis. Econ.* **2022**, *43*, 2875–2886. [CrossRef]
68. Karkošková, S. Data governance model to enhance data quality in financial institutions. *Inf. Syst. Manag.* **2023**, *40*, 90–110. [CrossRef]
69. Collibra Data Governance. Available online: https://www.collibra.com/us/en/products/datagovernance (accessed on 15 October 2023).
70. AXON DATA GOVERNANCE. Available online: https://www.informatica.com/gb/products/dataquality/axon-data%20governance.html (accessed on 15 October 2023).
71. Mahalle, P.N.; Hujare, P.P.; Shinde, G.R. Data Acquisition and Preparation. In *Predictive Analytics for Mechanical Engineering: A Beginners Guide*; Springer Nature: Singapore, 2023; pp. 11–38.
72. Marchand, D.A.; Kettinger, W.J.; Rollins, J.D. Information orientation, business agility, and digital transformation. *MIS Q.* **2018**, *42*, 591–616.
73. Gandomi, A.; Haider, M. Beyond the hype: Big data concepts, methods, and analytics. *Int. J. Inf. Manag.* **2015**, *35*, 137–144. [CrossRef]
74. Almeida, F.; Bacao, F.; Santos, M.F. Data-driven innovation: Concepts, approaches, and empirical evidence. *Inf. Syst. Manag.* **2019**, *36*, 99–114.
75. Kelleher, J.D.; Mac Namee, B.; D'Arcy, A. *Fundamentals of Machine Learning for Predictive Data Analytics: Algorithms, Worked Examples, and Case Studies*; MIT Press: Cambridge, MA, USA, 2015.
76. Floridi, L.; Cowls, J.; Beltrametti, M.; Chatila, R.; Chazerand, P.; Dignum, V.; Luetge, C.; Madelin, R.; Pagallo, U.; Rossi, F.; et al. AI4People—An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. *Minds Mach.* **2018**, *28*, 689–707. [CrossRef] [PubMed]
77. Marr, B. *Artificial Intelligence in Practice: How 50 Successful Companies Used AI and Machine Learning to Solve Problems*; Wiley: Hoboken, NJ, USA, 2019.
78. Davenport, T.H. *Process Innovation: Reengineering Work through Information Technology*; Harvard Business Review Press: Brighton, MA, USA, 2013.
79. Xiong, J.; Qin, G.; Liu, X.; Sun, X. Deep learning in personalized recommendation: A survey. *Proc. IEEE* **2019**, *107*, 15–37.
80. Phua, C.; Lee, V.; Smith, K.; Gayler, R. A comprehensive survey of data mining-based fraud detection research. *arXiv* **2010**, arXiv:1009.6119.
81. Zhu, X.; Zheng, Y.; Zhang, Z.; Li, J.; Yu, P.S. Deep learning for online advertising: A comprehensive review. *ACM SIGKDD Explor. Newsl.* **2020**, *22*, 5–20.
82. Najdawi, A.; Shaheen, A. Which Project Management Methodology is better for AI-Transformation and Innovation Projects? In Proceedings of the 2021 International Conference on Innovative Practices in Technology and Management (ICIPTM), Noida, India, 17–19 February 2021; IEEE: New York, NY, USA, 2021; pp. 205–210.
83. Holmström, J. From AI to digital transformation: The AI readiness framework. *Bus. Horiz.* **2022**, *65*, 329–339. [CrossRef]
84. Grebe, M.; Franke, M.R.; Heinzl, A. Artificial intelligence: How leading companies define use cases, scale-up utilization, and realize value. *Inform. Spektrum* **2023**, 1–13. [CrossRef]
85. Neumann, O.; Guirguis, K.; Steiner, R. Exploring artificial intelligence adoption in public organizations: A comparative case study. *Public Manag. Rev.* **2023**, 1–28. [CrossRef]
86. Bharadiya, J.P. A Comparative Study of Business Intelligence and Artificial Intelligence with Big Data Analytics. *Am. J. Artif. Intell.* **2023**, *7*, 24.
87. Voss, N.; Falcone, M.; Witherow, R.; Tenreiro, N.; Gans, H.; Camburn, M. *Competency Modeling: An Essential Practice for the Future of Strategic Human Capital Management*; Society for Industrial and Organizational Psychology, Inc.: Columbus, OH, USA, 2022.
88. Li, B.; Qi, P.; Liu, B.; Di, S.; Liu, J.; Pei, J.; Yi, J.; Zhou, B. Trustworthy AI: From principles to practices. *arXiv* **2023**, arXiv:2110.01167. [CrossRef]
89. Zabala, C.; Javier, F. The Barriers for Implementing AI. In *Grow Your Business with AI: A First Principles Approach for Scaling Artificial Intelligence in the Enterprise*; Apress: Berkeley, CA, USA, 2023; pp. 85–110.
90. La Torre, D.; Colapinto, C.; Durosini, I.; Triberti, S. Team formation for human-artificial intelligence collaboration in the workplace: A goal programing model to foster organizational change. *IEEE Trans. Eng. Manag.* **2021**, *70*, 1966–1976. [CrossRef]
91. Heilig, T.; Scheer, I. Decision Intelligence: Transform Your Team and Organization with AI-Driven Decision-Making. John Wiley & Sons: Hoboken, NJ, USA, 2023.
92. Bawany, S. *Transforming the Next Generation Leaders: Developing Future Leaders for a Disruptive, Digital-Driven Era of the Fourth Industrial Revolution (Industry 4.0)*; Business Expert Press: New York, NY, USA, 2019.
93. Priya, K.; Akshara, Y.A.S.; Venkatesh, J. Instinctive Data Analysis in Machine Learning and Summary Exhibitor. In *Intelligent and Fuzzy Systems: Digital Acceleration and the New Normal—Proceedings of the INFUS 2022 Conference, July 19-21, Izmir, Turkey*; Springer Nature: Berlin/Heidelberg, Germany, 2022; Volume 2.

94. Rajamani, S.K.; Iyer, R.S. Machine Learning-Based Mobile Applications Using Python and Scikit-Learn. In *Designing and Developing Innovative Mobile Applications*; IGI Global: Beijing, China, 2023; pp. 282–306.
95. Apache Spark. Available online: https://spark.apache.org/ (accessed on 16 December 2023).
96. Liu, Y.H. *Python Machine Learning by Example: Build Intelligent Systems Using Python, TensorFlow 2, PyTorch, and Scikit-Learn*; Packt Publishing Ltd.: Birmingham, UK, 2020.
97. Zeng, Y.; Zhang, J. A machine learning model for detecting invasive ductal carcinoma with Google Cloud AutoML Vision. *Comput. Biol. Med.* **2020**, *122*, 103861. [CrossRef]
98. Daugėla, K.; Vaičiukynas, E. Real-Time Anomaly Detection for Distributed Systems Logs Using Apache Kafka and H_2O.ai. In Proceedings of the International Conference on Information and Software Technologies, Kaunas, Lithuania, 13–15 October 2022; Springer International Publishing: Cham, Switzerland, 2022; pp. 33–42.
99. Etaati, L.; Etaati, L. Azure machine learning studio. In *Machine Learning with Microsoft Technologies: Selecting the Right Architecture and Tools for Your Project*; Springer: Berlin/Heidelberg, Germany, 2019; pp. 201–223.
100. TensorFlow. TensorFlow Serving Guide. Available online: https://www.tensorflow.org/tfx/guide/serving (accessed on 21 December 2023).
101. Amazon Web Services. Amazon SageMaker | Build, Train, and Deploy Machine Learning Models. Available online: https://aws.amazon.com/sagemaker/ (accessed on 21 December 2023).
102. Klaffenbach, F.; Michalski, O.; Klein, M.; Wali, M.; Tanasseri, N.; Rai, R. *Implementing Azure: Putting Modern DevOps to Use: Transform Your Software Deployment Process with Microsoft Azure*; Packt Publishing Ltd.: Birmingham, UK, 2019.
103. Google Cloud. AutoML—Google Cloud. Available online: https://cloud.google.com/automl (accessed on 21 December 2023).
104. H2O.ai. H2O Driverless AI—H2O.ai. Available online: https://h2o.ai/platform/ai-cloud/make/h2o-driverless-ai/ (accessed on 21 December 2023).
105. DataRobot. DataRobot: Augmented Machine Learning Platform. Available online: https://www.datarobot.com/ (accessed on 21 December 2023).
106. Tableau. Tableau: Business Intelligence and Analytics Software. Available online: https://www.tableau.com/ (accessed on 21 December 2023).
107. Microsoft. Power BI | Interactive Data Visualization BI Tools. Available online: https://powerbi.microsoft.com/en-gb/ (accessed on 21 December 2023).
108. Seaborn. Seaborn: Statistical Data Visualization. Available online: https://seaborn.pydata.org/ (accessed on 21 December 2023).
109. NLTK. Natural Language Toolkit—NLTK 3.6.5 Documentation. Available online: https://www.nltk.org/ (accessed on 21 December 2023).
110. spaCy. spaCy · Industrial-Strength Natural Language Processing in Python. Available online: https://spacy.io/ (accessed on 21 December 2023).
111. Google Cloud. Cloud Natural Language | Cloud Natural Language API | Google Cloud. Available online: https://console.cloud.google.com/apis/library/language.googleapis.com (accessed on 21 December 2023).
112. OpenCV. Available online: https://www.opencv.ai/ (accessed on 21 December 2023).
113. TensorFlow. TensorFlow Object Detection API. Available online: https://tensorflow-object-detection-api-tutorial.readthedocs.io/en/latest/ (accessed on 21 December 2023).
114. Azure. Computer Vision | Microsoft Azure. Available online: https://azure.microsoft.com/en-gb/products/cognitive-services/computervision (accessed on 21 December 2023).
115. Run:AI. NVIDIA A100 GPU: Overview, Benchmarks, and Buying Guide | Run:AI. Available online: https://www.run.ai/guides/nvidia-a100/nvidia-jetson (accessed on 21 December 2023).
116. Coral. Coral—Edge TPU—Google Coral. Available online: https://coral.ai/ (accessed on 21 December 2023).
117. SHAP. SHAP (SHapley Additive exPlanations). Available online: https://shap.readthedocs.io/en/latest/ (accessed on 21 December 2023).
118. IBM. AI Explainability 360 | IBM OSS. Available online: https://www.ibm.com/opensource/open/projects/ai-explainability/ (accessed on 21 December 2023).
119. Apache. Apache Airflow. Available online: https://airflow.apache.org/ (accessed on 21 December 2023).
120. AWS. AWS Glue—Data Extraction, Transformation, and Loading (ETL)—Amazon Web Services. Available online: https://aws.amazon.com/glue/ (accessed on 21 December 2023).
121. Google Cloud. Cloud Dataflow: Stream & Batch Data Processing | Google Cloud. Available online: https://cloud.google.com/dataflow (accessed on 21 December 2023).
122. MLflow. MLflow | An Open Platform to Manage the Machine Learning Lifecycle. Available online: https://mlflow.org/ (accessed on 21 December 2023).
123. DVC. Data Version Control—DVC 2.0.17 Documentation. Available online: https://dvc.org/ (accessed on 21 December 2023).
124. Git Large File Storage. Git Large File Storage. Available online: https://git-lfs.com/ (accessed on 21 December 2023).
125. Wright, B. 'Happily ever After?' Readiness for Change amongst Managers in Regard to the Adoption of AI within an International Bank. Ph.D. Dissertation, Edinburgh Napier University, Edinburgh, UK, 2022.
126. Rawashdeh, A. The consequences of artificial intelligence: An investigation into the impact of AI on job displacement in accounting. *J. Sci. Technol. Policy Manag.* **2023**. [CrossRef]

127. Fountaine, T.; McCarthy, B.; Saleh, T. Building the AI-powered organization. *Harv. Bus. Rev.* **2019**, *97*, 62–73.
128. Watson, G.J.; Desouza, K.C.; Ribiere, V.M.; Lindič, J. Will AI ever sit at the C-suite table? The future of senior leadership. *Bus. Horiz.* **2021**, *64*, 465–474. [CrossRef]
129. Seenivasan, D. ETL (Extract, Transform, Load) Best Practices. *Int. J. Comput. Trends Technol.* **2023**, *71*, 40–44. [CrossRef]
130. Apache Kafka. Available online: https://kafka.apache.org/ (accessed on 21 December 2023).
131. Talend. Data Integration, Big Data, and Cloud Integration Platform | Talend. Available online: https://www.talend.com/ (accessed on 21 December 2023).
132. Informatica. Informatica: Data Integration Leader for Big Data & Cloud Analytics. Available online: https://www.informatica.com/ (accessed on 21 December 2023).
133. Milo, T.; Somech, A. Automating exploratory data analysis via machine learning: An overview. In Proceedings of the 2020 ACM SIGMOD International Conference on Management of Data, Portland, OR, USA, 14–19 June 2020; pp. 2617–2622.
134. Singh, C.; Gaba, N.S.; Kaur, M.; Kaur, B. Comparison of different CI/CD tools integrated with cloud platform. In Proceedings of the 2019 9th International Conference on Cloud Computing, Data Science & Engineering (Confluence), Noida, India, 10–11 January 2019; IEEE: New York, NY, USA, 2019; pp. 7–12.