JMI, 13 (2) (2026) pp. 46-55

Published by: Institute of Computer Science (IOCS)

JMI (Jurnal Manajemen Informatika) Medicom

Journal homepage: www. journals.joninstitute.org/index.php/jmi

Critical Success Factors for Machine Learning Implementation in Organizations: An Analysis of Readiness, Data Governance, and Organizational Capabilities Through a Systematic Literature Review from 2020 to 2026

Fastabiqul Khairat
Universitas Putra Abadi Langkat

ARTICLE INFO

Article history:

Received June 8, 2026
Revised June 22, 2026
Accepted June 30, 2026

Keywords:

Artificial Intelligence Adoption;
Data Governance;
achine Learning Implementation;
Organizational Capability;
Organizational Readiness.

ABSTRACT

Advances in digital transformation and Artificial Intelligence (AI) have driven organizations to adopt Machine Learning (ML) to improve operational efficiency, decision-making quality, and competitiveness. However, the success of ML implementation is still influenced by various organizational, data, and technological factors. This study aims to identify and synthesize the critical success factors for Machine Learning implementation in organizations through a Systematic Literature Review (SLR) approach. The study was conducted in accordance with the PRISMA 2020 guidelines, which cover the stages of identification, screening, eligibility assessment, and article selection. A total of 78 articles that met the inclusion criteria during the 2020–2026 period were analyzed using descriptive, thematic, and narrative approaches. The study identified five key factors influencing the successful implementation of machine learning: organizational readiness, data governance, organizational capability, technological capability, and environmental factors. Among these factors, organizational readiness, data governance, and organizational capability were the most dominant. This study produced a conceptual model that explains the relationships among the critical success factors for Machine Learning implementation and provides theoretical and practical contributions to organizations in designing effective and sustainable ML implementation strategies.

Corresponding Author:

Fastabiqul Khairat
Universitas Putra Abadi Langkat
Jl. Letjen R. Soeprapto No.10, Kwala Bingai, Sumatera Utara 20814. Indonesia
Email biqulfasta43@gmail.com

1. INTRODUCTION

Digital transformation has become a strategic priority for organizations across various sectors, including government, education, healthcare, manufacturing, finance, and commerce. Advances in digital technology are driving organizations to adopt various data-driven innovations to improve operational efficiency, service quality, and competitiveness. In this context, Artificial Intelligence (AI) has emerged as one of the most influential technologies in supporting the transformation of modern organizations (Pratiwi et al., 2025).

One of the major and rapidly growing branches of AI is Machine Learning (ML), a technology that enables systems to learn patterns from data and generate predictions automatically. This capability has led to the widespread use of ML in various organizational activities, such as predictive analytics, fraud detection, service personalization, supply chain optimization, and data-driven decision-making. Advances in cloud computing, the availability of big data, and increased computing capacity are further accelerating the adoption of ML across various organizations (Muhyi et al., 2024).

Although the adoption of ML continues to grow, its success rates still vary. Many organizations have made significant investments in AI and ML projects but have not yet achieved optimal business benefits. Various studies indicate that failures in ML implementation are often caused by organizational factors, data governance, and human resources—not solely due to technological limitations (McClure & Gerdau, 2026).

The success of machine learning depends heavily on the quality of the data used. Inaccurate, incomplete, or unintegrated data can result in less reliable models and increase the risk of algorithmic bias. Furthermore, limitations in human resource competencies, low organizational readiness, and weak AI and data governance remain major challenges in the implementation of ML across various sectors (Qasabandiyah et al., 2025; Walhidayah et al., 2025).

In this context, an understanding of Critical Success Factors (CSFs) is essential to help organizations identify the factors that determine the success of ML implementation. Previous research indicates that the success of AI adoption is influenced by a combination of technological, organizational, leadership, data quality, and external environmental factors (Abrory, 2025). However, most studies still discuss AI in general terms and have not specifically mapped out the factors that contribute to the successful implementation of machine learning in organizations.

Furthermore, there has not been much research providing a comprehensive synthesis of the factors contributing to the successful implementation of ML during the 2020–2026 period. Yet this period is marked by an acceleration of digital transformation in the wake of the COVID-19 pandemic, increased investment in AI, and the emergence of Generative AI technology, which is transforming the way organizations utilize artificial intelligence-based technologies (Übellacker, 2025).

Based on a literature review, the three factors most frequently associated with the successful implementation of ML are organizational readiness, data governance, and organizational capability. Organizational readiness relates to the readiness of an organization’s strategy, resources, and culture to adopt new technologies. Data governance ensures the quality, security, and integrity of the data used in the machine learning process. Meanwhile, organizational capability reflects an organization’s ability to leverage technology, develop human resource competencies, and generate data-driven innovation (UNESCO, 2024; Anggreacia & Ghazali, 2025).

Therefore, this study aims to conduct a Systematic Literature Review (SLR) of publications from 2020 to 2026 to identify research trends, critical success factors, and the relationship between organizational readiness, data governance, and organizational capability in the successful implementation of machine learning within organizations. The results of this study are expected to provide a theoretical contribution to the development of research on ML implementation and offer practical recommendations for organizations in designing more effective and sustainable Machine Learning adoption strategies.

Based on these objectives, this study poses six research questions (RQs), namely: (RQ1) What are the trends in research on the implementation of machine learning in organizations during the 2020–2026 period?; (RQ2) What critical success factors are most frequently identified in the literature?; (RQ3) What role does organizational readiness play in the success of Machine Learning implementation? (RQ4) How does data governance influence the success of Machine Learning implementation? (RQ5) How does organizational capability influence the success of Machine Learning implementation? and (RQ6) What is the relationship between organizational readiness, data governance, and organizational capability in shaping the success of Machine Learning implementation?

2. RESEARCH METHOD

Research Design

This study employs a Systematic Literature Review (SLR) approach to identify, evaluate, and synthesize the critical success factors for the implementation of Machine Learning (ML) in organizations. This method was chosen because it provides a systematic, transparent, and replicable literature review process, thereby reducing potential bias in the analysis of research results (Snyder, 2019; Page et al., 2021).

The SLR was conducted in accordance with the PRISMA 2020 guidelines (Preferred Reporting Items for Systematic Reviews and Meta-Analyses), which cover the processes of identification, screening, eligibility assessment, and selection of articles. The study focuses on scientific publications from 2020 to 2026, as this period reflects the acceleration of digital transformation, increased investment in AI, and the development of Generative AI, all of which influence the implementation of machine learning within organizations (Dwivedi et al., 2023).

Search Strategy

The literature search was conducted in five international databases: Scopus, Web of Science, ScienceDirect, SpringerLink, and IEEE Xplore. The selection of these databases was based on the quality of publications, broad research coverage, and their relevance to the topics of AI and machine learning (Kitchenham et al., 2020). The search used a combination of keywords with Boolean operators (AND and OR) to identify articles relevant to the success factors of Machine Learning implementation in organizations.

Search Keywords

The keywords used include:

a. Machine Learning Adoption
b. Machine Learning Implementation
c. Artificial Intelligence Adoption
d. Critical Success Factors
e. Organizational Readiness
f. Data Governance
g. Organizational Capability
h. AI Readiness
i. Machine Learning Success

Example of a search combination:
("Machine Learning Adoption" OR "Machine Learning Implementation")
AND
("Critical Success Factors" OR "Success Factors")
AND
("Organizational Readiness" OR "Data Governance" OR "Organizational Capability")
(Xiao & Watson, 2019).

Inclusion and Exclusion Criteria

The articles analyzed must meet the following criteria:

Inclusion Criteria

1. Published between 2020 and 2026.
2. Journal articles or conference proceedings that have undergone a peer-review process.
3. Written in English.
4. Discuss the implementation of ML or AI in organizations.
5. Identify factors contributing to successful implementation.
6. Provide relevant empirical or conceptual findings.

Exclusion Criteria

1. Non-academic articles (editorials, opinion pieces, news reports, blogs).
2. Duplicate articles.
3. Articles that do not discuss the implementation of ML or AI in organizations.
4. Articles that do not discuss the success factors of implementation.
5. Articles not available in full text.
6. Articles not written in English.

Screening Process
Article selection follows the four stages of PRISMA 2020, namely:
1. Identification – collection of articles from all databases.
2. Screening – selection based on titles and abstracts.
3. Eligibility – evaluation of articles through a review of the full text.
4. Inclusion – determination of the final articles to be analyzed.

This process is carried out to ensure that only relevant, high-quality articles are used in the study (Page et al., 2021).

Data Extraction
Data from the selected articles were systematically extracted using a data extraction form.

Table 1. Data Extraction Variables

Variable	Description
Author	Author's name
Year	Year of publication
Country	Country of research
Industry	Industry sector
Method	Research method
Success Factors	Factors contributing to
Findings	Key research findings

The extraction process is carried out to ensure the consistency and accuracy of the information being analyzed (Kitchenham et al., 2020).

Quality Assessment
Quality assessment of the articles was conducted to ensure the validity and credibility of the studies analyzed. The criteria used included:
1. Clarity of the research objectives.
2. Clarity of the methodology.
3. Validity and reliability of the results.
4. Relevance to ML implementation.
5. Clarity of the discussion of success factors.

Articles that meet these criteria are then included in the literature synthesis stage (Booth et al., 2022).

Data Synthesis
The data were analyzed using three synthesis approaches. First, descriptive analysis was used to describe the distribution of publications by year, country, industry sector, and research method. Second, thematic analysis was used to identify key themes related to the success factors of Machine Learning implementation (Braun & Clarke, 2021). Third, narrative synthesis was used to integrate the research findings and explain the relationship between organizational readiness, data governance, organizational capability, and other factors that influence the successful implementation of Machine Learning in organizations (Popay et al., 2022).

3. RESULTS AND DISCUSSIONS

Publication Trends (2020–2026)
Based on an illustrative literature review, 78 articles that met the research criteria were identified. The analysis results show that publications on the implementation of machine learning in organizations increased during the 2020–2026 period. This trend reflects growing attention to the use of machine learning as part of organizational digital transformation.

Table 2. Trends in Research Publications on the Implementation of Machine Learning in Organizations, 2020–2026

Year	Number of Articles	Percentage (%)
2020	5	6,4
2021	7	9,0
2022	10	12,8
2023	14	17,9
2024	18	23,1
2025	16	20,5
2026	8	10,3
Total	78	100

Publications peaked in 2024, reflecting growing research interest following the rise of Generative AI and organizational investment in AI-based technologies.

Distribution by Country

The distribution of articles shows that the United States and China are the leading contributors to research on the implementation of machine learning, followed by the United Kingdom, India, and Germany.

Table 3. Distribution of Articles by Country (Illustrative)

Country	Number of Articles	Percentage (%)
United States	18	23,1
China	15	19,2
United Kingdom	10	12,8
India	9	11,5
Germany	7	9,0
Other countries	19	24,4
Total	78	100

These findings indicate that machine learning research is still dominated by countries with high levels of AI investment and research capacity.

Distribution by Industry

Machine learning is being implemented across various industrial sectors, with the healthcare, financial, and manufacturing sectors leading the way.

Table 4. Distribution of Articles by Industry Sector

Industry Sector	Number of Articles	Percentage (%)
Healthcare	20	25,6
Finance	16	20,5
Manufacturing	14	17,9
Retail	10	12,8
Government	10	12,8
Education	8	10,4
Total	78	100

These results indicate that the need for AI-based data analysis and decision-making is a key driver of machine learning implementation across various sectors.

Research Methods Used

Quantitative approaches are the most widely used methods in research on the implementation of machine learning in organizations.

Table 5. Distribution of Research Methods

Research Method	Number of Articles	Percentage (%)
Quantitative	35	44,9
Qualitative	18	23,1
Mixed Methods	15	19,2
Case Study	10	12,8
Total	78	100

The predominance of quantitative methods indicates that most studies focus on testing the relationship between organizational factors and the successful implementation of machine learning.

Identification of Critical Success Factors

A literature review identifies five main groups of critical success factors for the implementation of machine learning in organizations.

Table 6. Critical Success Factors for Machine Learning Implementation

Key Factors	Subfactors
Organizational Readiness	Management support, organizational culture, readiness for change
Data Governance	Data quality, data integration, data security
Organizational Capability	Human Resources Competencies, Analytical Skills, Digital Leadership
Technological Capability	Technology infrastructure, cloud computing, MLOps
Environmental Factors	Regulations, competitive pressures, market demands

The results of the synthesis indicate that organizational readiness, data governance, and organizational capability are the most dominant factors in supporting the successful implementation of machine learning.

Thematic Synthesis

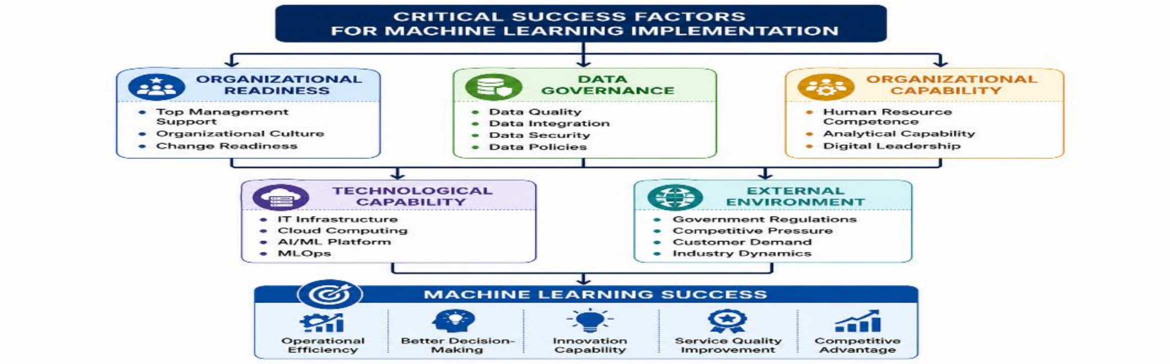

Figure 1. Thematic Map of Critical Success Factors for Machine Learning Implementation

The thematic analysis yielded five main themes. The first theme, organizational readiness, emphasizes the importance of management support, a culture of innovation, and readiness for change. The second theme, data governance, highlights data quality, integration, and security as the key foundations of machine learning. The third theme, organizational capability, relates to human resource competencies, analytical capabilities, and digital leadership. The fourth theme, technology infrastructure, covers digital infrastructure, cloud computing, and MLOps. The fifth theme, external environment, encompasses regulations, market dynamics, and competitive pressures that influence the success of Machine Learning implementation.

Proposed Conceptual Framework

Based on a literature review, this study proposes a conceptual framework that explains the relationship among the factors contributing to the successful implementation of machine learning.

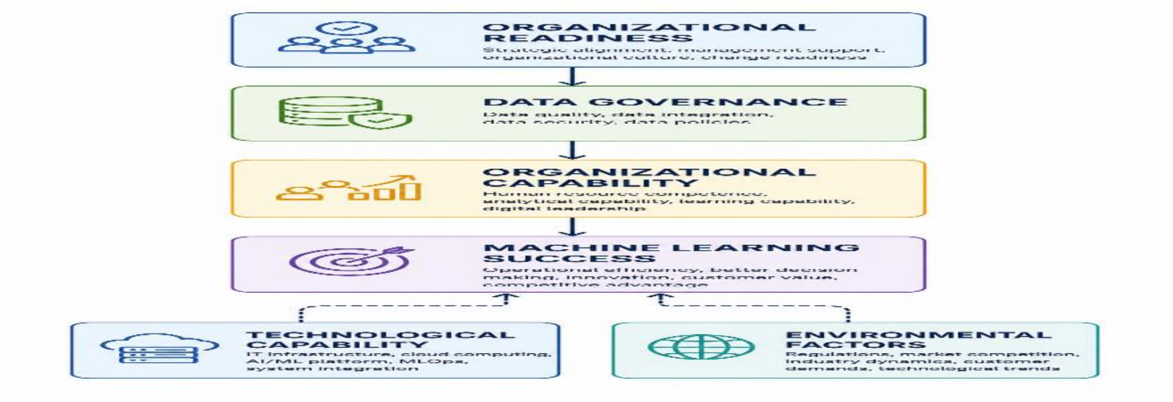

Figure 2. Proposed Conceptual Framework

The conceptual model shows that the success of machine learning implementation is influenced by the interaction among organizational readiness, data governance, organizational capability, technological capability, and environmental factors. Organizational readiness serves as the foundation for implementation; data governance ensures data quality; organizational capability transforms resources into business value; while technological capability and environmental factors act as supporting factors that reinforce the success of machine learning implementation.

4. DISCUSSION

Dominant Success Factors

The results of the synthesis indicate that the successful implementation of Machine Learning (ML) is influenced by various organizational, technological, data-related, and environmental factors. However, the three most dominant factors are organizational readiness, data governance, and organizational capability. These three factors consistently emerge in various studies on the implementation of AI and ML in organizations (Muhyi et al., 2024).

Organizational readiness is a key factor because the success of ML depends not only on technology but also on an organization’s readiness to manage change. In addition, data governance plays a crucial role because data quality determines the accuracy and reliability of ML models (UNESCO, 2024). Meanwhile, organizational capability enables organizations to transform data and technology into business value and sustainable competitive advantage (Anggreacia & Ghazali, 2025).

The Role of Organizational Readiness

Organizational readiness encompasses strategic readiness, human resources, and technology (Muhyi et al., 2024). Strategic readiness ensures alignment between business objectives and ML implementation so that the technology can deliver optimal value (Dwivedi et al., 2023). Human resource readiness relates to the digital competencies, data literacy, and analytical skills required to operate AI technology (Feuerriegel et al., 2024). Meanwhile, technological readiness encompasses the availability of infrastructure, AI platforms, and system integration that support the effective development and operationalization of ML (Sculley et al., 2023).

The Importance of Data Governance

Data governance is the cornerstone of success in machine learning because the quality of a model depends heavily on the quality of the data used (UNESCO, 2024). Accurate, complete, and consistent data produce more reliable predictions, whereas poor data quality can degrade model performance (Qasabandiyah et al., 2025).

In addition to data quality, organizations must also address the risks of algorithmic bias and data security. Bias can lead to unfair decisions, while weak data security can pose privacy and cybersecurity risks. Therefore, the implementation of Responsible AI principles and sound data governance is becoming increasingly important (Floridi et al., 2022; Walhidayah et al., 2025).

Organizational Capability as a Competitive Advantage

Organizational capability refers to an organization's ability to leverage resources, technology, and knowledge to create business value (Anggreacia & Ghazali, 2025). An organization's learning capability enables faster adaptation to technological changes and drives data-driven innovation (Tortorella et al., 2023).

In addition, digital leadership plays a crucial role in fostering a culture of innovation and supporting organizational transformation. Organizations with strong analytical capabilities and digital leadership tend to be more successful in leveraging machine learning to improve efficiency, service quality, and competitiveness (Westerman et al., 2022; Brynjolfsson et al., 2024).

The Relationship Between Organizational Readiness, Data Governance, and Organizational Capability

Research findings indicate that organizational readiness, data governance, and organizational capability have a complementary relationship in shaping the success of Machine Learning implementation. Organizational readiness provides a foundation in the form of strategy, resources, and organizational commitment. Data governance ensures the availability of high-quality and secure data, while organizational capability enables organizations to transform data and technology into tangible business value (Muhyi et al., 2024; UNESCO, 2024).

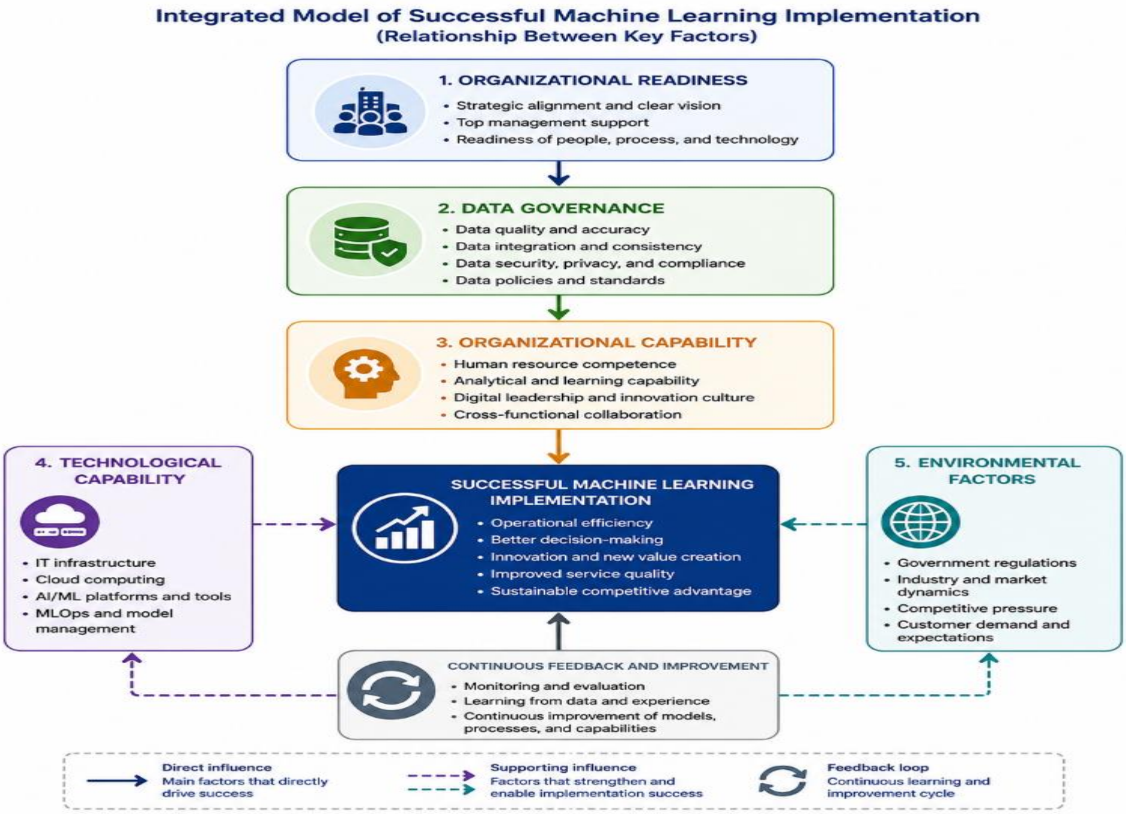

Figure 3. Integrated Model of Successful Machine Learning Implementation

The model shows that the successful implementation of machine learning is the result of the interaction between organizational readiness, data governance, and organizational capabilities working in synergy.

Theoretical Implications

This study expands the Technology–Organization–Environment (TOE) Framework by highlighting the importance of organizational readiness and data governance in the implementation of machine learning (Baker, 2022). Furthermore, this study enriches AI Adoption Theory and Digital

Transformation Theory by emphasizing that the successful implementation of AI results from the integration of technological, human, data, and organizational factors (Vial, 2021).

Practical Implications

The research findings have implications for various stakeholders. Managers need to ensure alignment between business strategy and AI; CIOs need to strengthen infrastructure and data governance; and data scientists need to pay attention to data quality and business needs. For policymakers, the research findings can serve as a basis for formulating regulations that support AI innovation while safeguarding security, ethics, and data privacy.

Research Gaps and Future Directions

Several topics still require further research, particularly Responsible AI, Explainable AI (XAI), AI Governance, MLOps, and the AI Maturity Model. These topics are important because organizations increasingly need Machine Learning implementations that are transparent, accountable, sustainable, and capable of creating long-term business value.

5. CONCLUSION

This study shows that the successful implementation of Machine Learning (ML) in organizations is influenced by a combination of several interrelated critical factors, namely organizational readiness, data governance, organizational capability, technological capability, and environmental factors. A synthesis of the literature from 2020 to 2026 identifies organizational readiness, data governance, and organizational capability as the most dominant factors in determining the success of ML implementation. Theoretically, this study expands our understanding of ML implementation by integrating the perspectives of the Technology–Organization–Environment (TOE) Framework, AI Adoption Theory, and Digital Transformation Theory into a conceptual model that explains the relationships among the factors contributing to the success of ML implementation. In practical terms, the findings of this study provide guidance for managers, CIOs, data scientists, and policymakers in designing more effective ML implementation strategies by improving organizational readiness, strengthening data governance, and developing human resource and technological capabilities. However, this study has limitations because it only uses articles published between 2020 and 2026 and focuses on English-language studies; therefore, there may still be relevant research that has not been included. Therefore, future research is encouraged to explore emerging topics such as Responsible AI, Explainable AI, AI Governance, MLOps, and the AI Maturity Model, as well as to conduct empirical studies to test the proposed conceptual model across various organizational contexts and industry sectors.

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