The Role of Machine Learning Adoption in Enterprises: Literature Review and European Insights

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Abstract: Machine learning (ML) represents one of the most transformative technologies shaping modern business environments. Its ability to process large volumes of data and generate predictive insights offers new opportunities for data-driven decision making and strategic management. However, despite its growing potential and benefits, the actual adoption of ML in enterprises remains relatively limited. The aim of this paper is to explore the current state of ML adoption across enterprises in the European Union and to synthesize existing research on how ML is applied in different business functions. Using secondary data from Eurostat and a structured literature review, the study identifies key areas of implementation, major benefits, and persistent barriers that influence the adoption and effective use of ML in organizations. Findings suggest that while ML enhances accuracy, efficiency, and strategic agility, its diffusion in European enterprises is still constrained by data related challenges, implementation costs, and shortages of skilled professionals. The paper underscores that closing widening cross-country gaps and moving beyond pilot stages will require stronger data pipelines and stewardship, practical model explainability, and change management to scale ML across enterprises, especially in lagging sectors such as manufacturing and transportation.

Keywords: Machine learning, EU, business functions
JEL Classification: L86, M21, O33

1 Introduction

Recently, the adoption of artificial intelligence (AI) has been the subject of intense research, focusing on the drivers and barriers to its deployment, as well as its wider economic and social consequences. AI has evolved from largely theoretical concepts into a technology that increasingly forms the 'foundational layer' of the digital economy. Central to this development is machine learning (ML), a practical mechanism that converts data into predictions and decisions, combining insights from statistics, optimization, and software engineering (Jordan & Mitchell, 2015 ; Russell & Norvig, 2021). ML is effectively a data-driven computational approach where algorithms learn from examples and improve over time without explicit rule programming. Consequently, the literature frequently characterizes it as the automation of knowledge extraction from data. (Bose & Mahapatra, 2001)

The European Union provides a compelling context for investigating AI/ML adoption, characterized by marked heterogeneity among member states regarding digitalization levels, data availability, innovation capacity, and the organizational readiness to absorb new technologies. This divergence translates into an uneven pace of AI deployment, notwithstanding the substantial potential for macroeconomic gains. While projections frequently indicate that widespread AI adoption could augment European economic activity by approximately one-fifth by 2030, realizing this growth is contingent upon the effective integration of these technologies at the firm level – encompassing processes, data, human capital, and management. (Bughin et al., 2019)

Public policy and regulatory frameworks serve as critical mechanisms that modulate national patterns of AI deployment. In an effort to cultivate a fertile environment for AI uptake, the EU has introduced strategic measures including the European AI Strategy and the Digital Compass 2030 framework (European Commission, 2021). However, the practical application

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of these directives is inconsistent, leading to significant divergence in the levels of AI preparedness observed across member states (Veale & Binns, 2017)

Yet real-world adoption remains uneven. The European Union offers a particularly suitable context for examining these technologies: its member states exhibit substantial diversity in levels of digitalization, data availability, and innovation capacity, enabling comparisons of the institutional and organizational conditions that shape ML deployment across economies of countries and sectors.

This article addresses that need with a two-part contribution. First, it assembles a current snapshot of ML adoption in EU enterprises using recent Eurostat indicators to outline the overall landscape across countries and sectors. Second, it complements this perspective with a targeted literature review that systematically maps how ML is deployed across key business functions, identifies the most common study designs and algorithmic approaches in prior research, and synthesizes the main constraints that continue to limit broader diffusion of machine learning within enterprises. To enhance analytical clarity and academic transparency, the study is structured around a set of explicit research questions. These questions reflect the dual approach of the paper:

RQ1: What is the current level and recent evolution of machine learning adoption among enterprises across EU Member States?

RQ2: What role does machine learning play in the most frequently addressed business functional areas within enterprises?

RQ3: What barriers and constraints to ML adoption are most frequently reported in the recent academic literature?

The findings have practical relevance for managers, by offering a decision-oriented framework for developing ML initiatives, for policymakers, by informing more targeted support measures, and for the academic community, by laying a basis for further empirical research and teaching.

2 Methods

The objective of this study is to analyze the current state of machine-learning adoption in enterprises across the European Union and to understand the principal business functions in which these technologies are being deployed. The first part of research analyzes secondary statistics from Eurostat (2021–2024), and the second part presents a literarute review of empirical and application-oriented studies, indexed in Web of Science, Scopus and Google Scholar.

In the Eurostat data analysis, the extent of machine-learning adoption (using „Artificial intelligence by NACE Rev. 2 activity“ - isoc_eb_ain2) is examined across EU member states for 2021–2024 (2022 was excluded due to a missing dataset). To capture adoption trends, an average growth index and quantified cross-country variability using the standard deviation is calculated.

Calculation formulas:

- growth ratios: $g1_i = \frac{x_{i,2023}}{x_{i,2021}}$, $g2_i = \frac{x_{i,2024}}{x_{i,2023}}$
- average growth index: $GI_i = \frac{g1_i + g2_i}{2}$
- standard deviation: sample SD using STDEV.S

Calculations and data processing were carried out in Microsoft Excel. ML adoption by sectors across the EU is visualized using chart.

The literature search employed combinations of keywords, pairing “machine learning” with “business,” “enterprise,” or “organization,” and with “implementation” or “adoption,” alongside functional qualifiers such as “marketing,” “finance,” “HR,” “manufacturing,” and “logistics.”

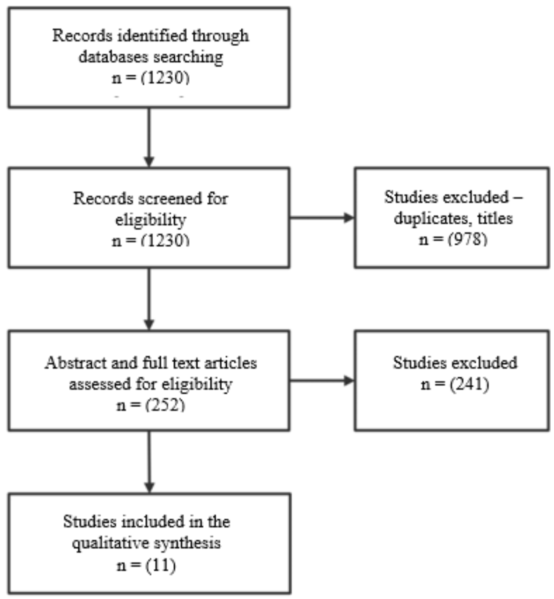
Inclusion criteria:

- Scholarly journal article or peer-reviewed conference paper

- Empirical application documenting real-world organizational use of ML (not purely theoretical modeling)
- Focus at least in part on a specific business function (e.g., marketing, finance, HR, manufacturing, logistics)
- Published between 2020 and 2025

The selected publications (11) were synthesized into a consolidated overview table organized by business function (Table 2). For each study, the empirical methodology is extracted, the types of ML models and algorithms applied, and the authors' key findings and implications for practice. Schematic diagram of the steps of the Literature review is shown in Figure 1.

Figure 1 Flow diagram of the Literature review



Source: Own processing

The final subsection of the Results section distills the main organizational and technical barriers observed across the evidence base and discusses their implications for successful ML adoption in firms.

3 Research results

The first part of the chapter focuses on identifying and analyzing ML adoption within enterprises across EU countries, as well as across individual sectors. The second subsection presents a literature review that identifies the main functional areas and practical modes of ML use. The analysis covers both the benefits of ML adoption and the barriers that constrain it.

3.1 Current state of Machine Learning adoption across EU countries

This subsection focuses on presenting the current state of machine-learning adoption in enterprises across EU member states. To better illustrate the evolution of adoption, an average growth index was employed, and to clarify the variability and cross-country differences in values, the standard deviation was used. The results are reported in Table 1.

Table 1 Percentage of enterprises using Machine learning technologies by European countries in the period 2021-2024

Countries	2021	2023	2024	AVG growth index
European Union	***2.44***	***2.60***	***4.24***	***1.3482***
Belgium	4.42	4.78	8.07	**1.3849**
Bulgaria	0.94	0.94	2.11	**1.6223**
Czechia	1.40	2.32	4.53	**1.8049**
Denmark	8.84	7.05	10.74	**1.1605**
Germany	2.87	2.97	5.26	**1.4029**
Estonia	1.08	1.60	3.53	**1.8439**
Ireland	3.53	2.98	5.53	**1.3499**
Greece	1.16	1.02	4.02	**2.4102**
Spain	2.32	2.96	3.91	**1.2984**
France	2.41	2.65	4.04	**1.3121**
Croatia	2.50	2.15	4.14	**1.3928**
Italy	1.45	1.51	2.57	**1.3717**
Cyprus	1.43	2.12	5.25	**1.9795**
Latvia	1.08	1.10	2.04	**1.4365**
Lithuania	1.19	1.28	2.80	**1.6316**
Luxembourg	3.48	3.93	6.28	**1.3636**
Hungary	0.72	0.98	1.82	**1.6091**
Malta	4.47	4.70	6.49	**1.2162**
Netherlands	6.05	5.82	6.52	**1.0411**
Austria	3.69	4.60	6.89	**1.3722**
Poland	0.74	1.02	1.56	**1.4539**
Portugal	1.98	2.06	2.88	**1.2192**
Romania	0.51	0.60	1.26	**1.6382**
Slovenia	3.21	2.88	4.19	**1.1760**
Slovakia	0.89	1.88	2.61	**1.7503**
Finland	6.10	6.51	9.68	**1.2771**
Sweden	4.43	3.96	8.09	**1.4684**
Norway	4.31	4.72	8.95	**1.4957**
Bosnia and Herzegovina	:	3.10	3.07	**-**
Montenegro	1.16	1.79	:	**-**
North Macedonia	0.90	:	:	**-**
Albania	:	:	:	**-**
Serbia	0.43	0.72	3.00	**2.9205**
Türkiye	1.18	2.27	2.32	**1.4729**
Standard deviation	**1.9783**	**1.7284**	**2.5267**	**-**

Source: Own processing based on the statistical data of Eurostat (2024)

Table 1 presents the evolution of ML adoption among enterprises in the European Union between 2021 and 2024 (year of 2022 is missing in the Eurostat database), based on data from Eurostat (2024). The indicator measures the proportion of enterprises using ML for data analysis, reflecting the degree of integration of advanced data-driven technologies into business processes. The results show that, on average, 2.44% of EU enterprises used ML in 2021, 2.60% in 2023, and 4.24% in 2024. This steady increase corresponds to an average growth index of 1.35, indicating a gradual but continuous diffusion of ML across the European business landscape. Nevertheless, the overall adoption level remains relatively low, suggesting that ML technologies are still in the early stages of business implementation compared to broader AI tools.

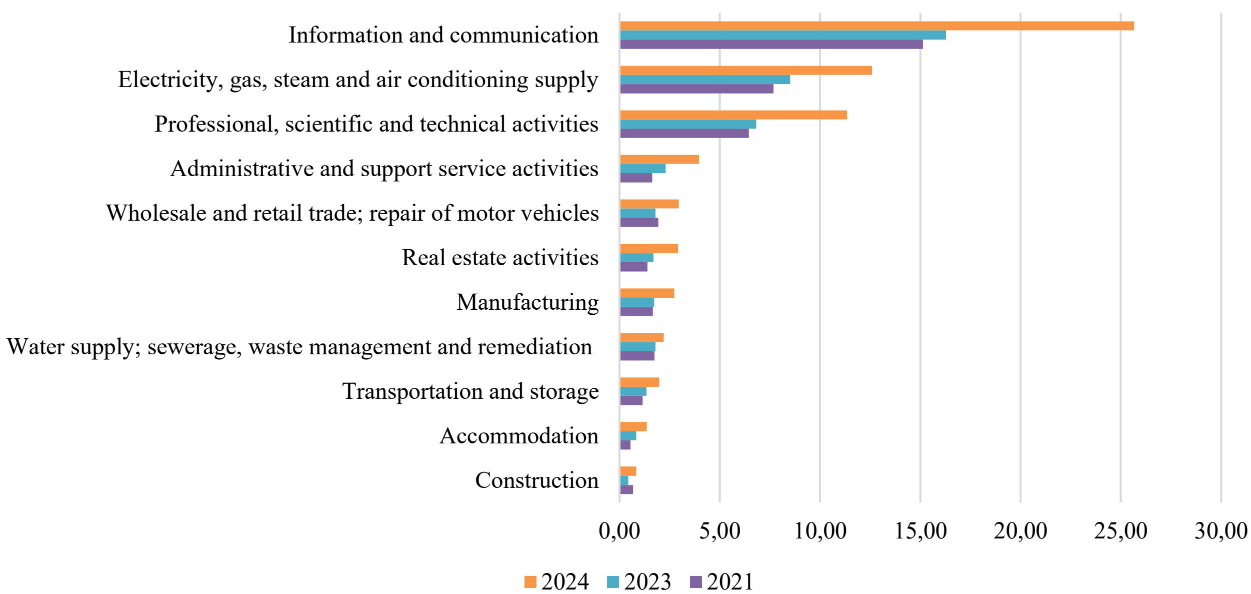
In terms of country performance, the highest ML adoption rates in 2024 were observed in Denmark (10.74%), Finland (9.68%), Norway (8.95%), Sweden (8.09%), and Belgium (8.07%). These countries belong to the group of digital frontrunners identified in previous studies (OECD, 2023; Eurostat, 2024), characterized by strong innovation ecosystems, advanced data infrastructure, and a high availability of digital skills. Their enterprises are typically more capable of incorporating ML solutions for predictive analytics, process automation, and decision support. In contrast, the lowest adoption rates were found in Romania (1.26%), Hungary (1.82%), Poland (1.56%), and Bulgaria (2.11%), reflecting persistent disparities in digital transformation and technological readiness across the EU. These patterns are consistent with findings from the Digital Economy and Society Index (DESI, 2023), which highlights a pronounced digital divide between Western/Northern Europe and Central/Eastern Europe.

The growth index reveals that several countries with initially low adoption levels experienced notable progress. For instance, Greece (2.41), Serbia (2.92), Cyprus (1.98), Estonia (1.84), and Czechia (1.80) recorded the fastest relative increases between 2021 and 2024, suggesting a catching-up effect in the adoption of advanced analytics. These improvements may be associated with targeted national strategies supporting digital innovation and EU-level initiatives under the Digital Europe Programme. Conversely, countries such as the Netherlands (1.04) and Denmark (1.16) show slower growth, which can be explained by their already mature level of ML diffusion, resulting in limited room for relative expansion.

From a statistical perspective, the standard deviation of adoption rates across EU countries increased from 1.98 in 2021 to 2.53 in 2024, indicating rising heterogeneity in ML diffusion. This growing variability suggests that while the overall trend is positive, the speed of adoption differs significantly between member states. The results thus confirm a positive but uneven trajectory in ML adoption: innovation leaders continue to advance towards deeper integration of ML into business strategies, whereas less digitally developed economies are still in the phase of initial implementation.

Building on the ML adoption analysis, a chart (Figure 2) visualizes the 2021–2024 trend across EU sectors.

Figure 2 Use of Machine learning technologies in enterprises by economic activity in the period 2021-2024



Source: Own processing based on the statistical data of Eurostat (2024)

Figure 2 shows the evolution of Machine Learning (ML) adoption across different sectors of economic activity in the European Union between 2021 and 2024, based on Eurostat (2024) data. The indicator captures the share of enterprises using ML or deep learning for data analysis. Overall, the use of ML technologies has increased across nearly all sectors during the observed period, though the growth has been highly uneven. In 2021, only a few sectors exceeded 5% adoption, whereas by 2024 several knowledge- and data-intensive industries achieved double-digit values.

The information and communication sector recorded the highest level of ML adoption, rising from 15.14% in 2021 to 25.66% in 2024. This reflects the sector's strong digital maturity, advanced data infrastructure, and direct engagement in technological innovation. Similarly, electricity, gas, steam and air conditioning supply reached 12.59%, and professional, scientific and technical activities increased from 6.46% to 11.35%, confirming that ML technologies are most widely used in sectors characterized by high information intensity and analytical capabilities. These industries rely on ML for predictive maintenance, energy optimization, data modeling, and research applications.

By contrast, more traditional and labor-intensive sectors show only marginal adoption levels. For example, construction (0.83%), accommodation (1.37%), and transportation and storage (1.98%) remain below the 2% threshold in 2024. Such sectors often face barriers including limited data availability, lower digitalization levels, and a shortage of skilled staff able to implement ML-based solutions. The manufacturing sector, although relatively advanced compared to other traditional industries, shows only moderate growth from 1.67% in 2021 to 2.73% in 2024, which suggests that ML adoption in production environments remains in its early stage and often limited to pilot projects or predictive maintenance systems.

Administrative and service-related sectors demonstrate intermediate adoption rates. For instance, administrative and support service activities grew from 1.63% to 3.96%, while real estate activities rose from 1.39% to 2.93%. This moderate progress indicates a growing interest in using ML for operational efficiency and customer data management, yet adoption remains constrained by organizational and resource limitations.

3.2 The role of Machine learning adoption in key business functions

The selection of relevant functional business areas was grounded in several studies, notably Pramanik & Jana (2022), who examined how machine learning can optimize enterprise processes across operations, supply chain, marketing, human resources, and customer relationship management. To synthesize the principal insights from the empirical literature, Table 2 provides a structured overview that specifies the business area, authors, year of publication, study title or objective, data and methodology, the machine learning algorithms employed, and the key findings/implications.

Table 1 Overview of empirical studies on ML in business functions

Enterprise Function	Author, Year	Title / Focus	Methodology	Algorithms / Approach	Key Findings
Manufacturing & Operations	Kaparthi & Bumblauskas (2020)	Designing predictive maintenance systems using decision tree-based ML	Empirical case-based system design	Decision Trees	Decision tree models are effective in modeling maintenance triggers and downtime prediction.
	Sauer, Burggräf & Steinberg (2024)	Bridging human expertise and machine learning in production management: a case study on ML-based decision support systems to prevent missing parts at assembly	Empirical case study of manufacturing assembly line using ML-DSS	ML-based DSS integrating human-expert feedback	The study demonstrates that the decision support system effectively aids complex decision-making, making it a valuable asset for contemporary manufacturing settings.
Supply Chain & Logistics	Leung et al. (2020)	Modelling near-real-time order arrival demand in e-commerce	Empirical ML modeling on e-commerce data	XGBoost, LSTM, Linear Regression	ML improves accuracy of short-term demand prediction in online retail operations.
	Zheng Y. (2024)	Application of ML Algorithms in Enterprise Supply Chain Demand Forecasting	Empirical with comparison of classical and ML models	LSTM, RF, SVR	ML outperforms traditional models in handling demand volatility and seasonality.
	Ferreira et al. (2025)	A Decision Support System for Classifying Suppliers Based on Machine Learning Techniques: A Case Study in the Aeronautics Industry	Case study using CRISP-DM on supplier data from aeronautics	K-Means, Hierarchical K-Means, AGNES, Fuzzy Clustering	Supplier segmentation via ML improved classification accuracy and supported supplier decision-making.
Finance & Risk Management	Yang A. (2025)	Big data-driven corporate financial forecasting and decision support	Deep learning with time-series financial datasets	CNN-LSTM	Hybrid models yield better forecast accuracy in financial planning and strategy.
	Parimi S. (2024)	Optimizing Financial Reporting and Compliance in SAP	Applied system integration + ML model training on SAP data	Decision Trees, SVM	ML improves anomaly detection and reporting efficiency in enterprise financial systems.
	Wyrobek, 2020	ML to identify companies with unfair corporate culture	Empirical study using financial disclosures	RF, XGBoost, Neural Nets, Decision Trees	Tree-based models effective at detecting unethical corporate behaviors.
Marketing & CRM	Sikri et al. (2024)	Enhancing customer retention in telecom via churn prediction	Empirical study with classification models	SVM, RF, Logistic Regression	ML models improve churn prediction and customer targeting in telecom.
HR & People Analytics	Tian et al. (2023)	ML-based HR recruitment system using BERT and SVM	System design + ML classification on resume datasets	LSA, BERT, SVM	ML improves resume screening accuracy and offers interpretable HR decisions.
	Hasan et al. (2024)	Employee Performance Prediction with Analytics and ML	Empirical model on HR metrics and performance reviews	Ensemble methods, Decision Trees	Integrated ML models accurately predict employee performance from historical records.

Source: Own processing

Table 2 identifies the principal domains and the role of machine learning across business functions. Based on a review of empirical studies, machine learning emerges as a universal and adaptable instrument that effectively supports decision making, optimizes business processes, and improves predictive accuracy across functional domains, as evidenced by findings in manufacturing, logistics, finance, marketing, and human resources. In manufacturing and operations, Kaparthi and Bumblauskas (2024) showed that decision-tree algorithms efficiently model maintenance triggers and predict downtime, thereby enhancing process reliability, while a case study by Sauer, Burggräf, and Steinberg (2024) demonstrated that implementing a decision support system based on machine learning and enriched with expert feedback materially improves complex decision processes in assembly-line management and constitutes a valuable tool for modern production environments. Within supply chains and logistics, Leung et al. (2020) demonstrated that XGBoost and LSTM enable more accurate real-time prediction of order arrivals in e-commerce and thus increase operational flexibility; similarly, Zheng (2024) confirmed that LSTM, Random Forest, and SVR outperform traditional forecasting approaches when processing seasonal and volatile demand data, and the case study by Ferreira et al. (2025) used K-means, AGNES, and fuzzy clustering to optimize supplier classification in the aerospace industry, thereby supporting more effective decision making across supply networks. In finance and risk management, Yang (2025) showed that deep neural architectures such as CNN-LSTM deliver higher accuracy in financial forecasting and provide a more robust basis for strategic planning, Parimi (2024) examined the integration of decision trees and SVM into SAP environments and documented efficiency gains in anomaly detection and financial reporting, and Wyrobek (2020) provided empirical evidence that Random Forest, XGBoost, and neural networks applied to firms' financial statements are effective in detecting unethical or fraudulent practices. In marketing and customer relationship management, Sikri et al. (2024) empirically demonstrated that SVM, Random Forest, and logistic regression substantially increase the accuracy of churn prediction and improve retention strategies, giving firms a competitive advantage through better personalization and customer segmentation. Finally, in human resources and people analytics, Tian et al. (2023) showed that combining BERT, LSA, and SVM improves the accuracy of résumé classification and yields interpretable recommendations for candidate selection, and Aboagarib et al. (2024) built on this work by using ensemble methods and decision trees to predict employee performance from historical HR metrics, thereby confirming the practical potential of machine learning for developing and managing human capital. Taken together, these studies indicate that machine learning approaches have not only theoretical relevance but also demonstrable empirical impact on performance improvement, cost optimization, and strategic decision support across corporate functions, fostering stronger data orientation within organizations, reducing decision uncertainty, and enabling innovative forms of organizational agility.

3.3 Main constraints and barriers of Machine learning adoption

Despite the mentioned advantages across individual business functions/areas, numerous studies point to barriers and potential constraints in the adoption of machine learning. Firms often lack sufficient high quality and well labeled data, face fragmented data architectures, and struggle to define concrete entry points for systematic data collection, which delays pilot viability and scale up (Giermindl et al., 2021; Jöhnk et al., 2020). Beyond data, organizations contend with the opaque logic of ML models that complicates error triage, accountability, and regulatory defensibility, which in turn suppresses trust among decision makers and slows deployment in sensitive domains (Benbya et al., 2021; Berente et al., 2021; Asatiani et al., 2021).

Early iterations of ML systems frequently underperform in the wild due to distribution shift and incomplete feature pipelines, which triggers defensive user responses and workflow workarounds, especially in high stakes settings such as healthcare where tolerance for false positives and false negatives is low and must be negotiated with frontline experts (Lebovitz et al., 2021; Benbya et al., 2021). These technical constraints are amplified by organizational capability gaps that include insufficient ML literacy, immature MLOps and governance processes, and a weak alignment between ML use cases and strategic objectives, a pattern documented across multiple industries and echoed in large scale practitioner surveys that rank data limitations, talent shortages, and integration with legacy systems as leading blockers (Jöhnk et al., 2020; Kaggle, 2020). Together these studies indicate that successful adoption requires concurrent investments in data pipelines and stewardship, mechanisms for model transparency and error discovery, iterative deployment with human in the loop learning, and change management that builds durable acceptance among both internal professionals and external stakeholders (Benbya et al., 2021; Berente et al., 2021).

4 Discussion

Section provides the clarifications and answers to the research questions:

RQ1: What is the current state and recent evolution of machine learning adoption among enterprises and sectors across EU Member States?

Current state indicates that the adoption of machine learning (ML) in EU enterprises is increasing but remains relatively low and increasingly uneven across countries: the EU average share of enterprises using ML for data analysis rose from 2.44% (2021) to 2.60% (2023) and then more markedly to 4.24% (2024), with the highest 2024 levels concentrated in digitally advanced economies (Denmark 10.74%, Finland 9.68%, Norway 8.95%, Sweden 8.09%, Belgium 8.07%), while the lowest shares persist in less digitally mature countries (Romania 1.26%, Poland 1.56%, Hungary 1.82%, Bulgaria 2.11%); although some countries show faster "catch-up" dynamics (based on growth indices), overall cross-country heterogeneity is widening, as reflected in the increase of the standard deviation from 1.98 (2021) to 2.53 (2024), suggesting that gaps in ML adoption across the EU are deepening rather than closing. These findings lend further support to the conclusions advanced by Ionașcu (2025), Mazurencu et al. (2025), and Drago et al. (2025), whose analyses based on Eurostat indicators of AI/ML uptake similarly portray adoption as steadily increasing yet still comparatively limited overall, while remaining markedly heterogeneous across Member States, with persistent clusters of frontrunners and laggards shaped by broader structural conditions within national economies.

RQ2: What role does machine learning play in the most frequently addressed business areas within enterprises?

Machine learning in the most frequently addressed business functional areas primarily plays the role of a predictive and decision-support layer, improving planning accuracy, increasing process efficiency, and partially automating routine decisions. In manufacturing and operations, it is used mainly for predictive maintenance and to support the management of production flows; in supply chain and logistics, for demand prediction and supplier segmentation/classification; in marketing and CRM, especially for customer churn prediction and personalization; and in finance, for forecasting as well as anomaly detection in reporting or compliance. In HR and people analytics, ML is applied to screening and evaluating candidates (e.g., CV processing) and to predicting employee performance based on historical data. Similar mappings of where ML is used in enterprises are also confirmed by other review and systematic studies across domains (e.g., predictive maintenance in manufacturing, AI in supply chains, ML in marketing, ML in financial risk/scoring, and AI in HRM). (Ngai & Wu, 2022; Douaioui et al., 2024; Benhanifa et al., 2025)

RQ3: What barriers and constraints to ML adoption are most frequently reported in the recent academic literature?

Key barriers to ML adoption include, first and foremost, data-related constraints – limited availability of high-quality, consistent, and accessible data, together with underdeveloped data pipelines and infrastructure – which directly undermine model reliability and impede scaling beyond initial use cases. A second major obstacle concerns capability gaps, namely the shortage of qualified personnel and in-house expertise in data and ML, which is often compounded by high implementation costs and the complexity of integrating ML into legacy systems, including the establishment of MLOps practices and robust lifecycle governance. In addition, trust, transparency, and explainability remain critical. These factors help explain why ML initiatives frequently remain at the pilot stage and why cross-country and cross-sector adoption gaps tend to persist or even widen.

5 Conclusions

The findings indicate that ML adoption among EU enterprises is on a steadily positive trajectory, yet the gap between countries is widening as traditional leaders with strong digital infrastructure and capabilities, notably the Nordic states and the Benelux, advance more rapidly, while several Central and Eastern European countries lag behind, even though some late adopters show signs of catching up. Sectorally, uptake is highest where data and process maturity are strong, for example in information and communications, in professional, scientific and technical activities, and in energy, whereas traditionally labor-intensive industries such as construction, accommodation and food services, and parts of transport trail behind; manufacturing is progressing more gradually, suggesting that many initiatives remain at the pilot stage. The overview table further shows that the greatest benefits are concentrated in functional areas such as operations, particularly predictive maintenance and quality, supply chain through demand forecasting and inventory management, marketing and CRM via churn prediction and personalization, finance and risk through anomaly detection and risk signals, and HR through talent selection and performance assessment, with ML improving decision making, predictive accuracy, automating routine decisions, and more tightly linking analytics with strategy. Despite this potential, barriers persist in the form of insufficient data readiness, limited model transparency, weaker initial performance in real-world settings, and organizational constraints in ML operations, governance, and skills, which directly explain uneven adoption across countries and the modest uptake in several traditional sectors including manufacturing. Embedding ML into everyday processes therefore requires parallel investment in data pipelines and stewardship, practical model explainability, and change management that can convert pilot initiatives into scaled, value-creating solutions.

This paper has three main limitations. First, the Eurostat analysis relies on secondary, aggregate data with cross-country measurement differences and a missing 2022 series, which limits comparability; the analysis focuses on a single indicator of ML use, which may not fully capture the broader scope. Moreover, the underlying Eurostat survey is based on a specific sample of enterprises rather than the full population, and responses are self-reported, meaning that reported ML use may reflect subjective interpretation and uneven reporting practices across countries. Second, the literature review is based on a subjective selection of relevant studies from 2020–2025 drawn from WoS, Scopus, and Google Scholar, which may introduce selection and publication bias. Third, without primary empirical research, the key mechanisms of ML adoption are inferred rather than directly observed. Future research should employ advanced statistical methods and structured interviews.

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