

Adoption Frequencies of Expert-Driven Learning-Based AI Taxonomy among R&D SMEs and Start-ups in Türkiye

Türkiye'deki Ar-Ge Merkezli KOBİ ve Girişimlerde Uzman Odaklı Öğrenmeye Dayalı YZ Taksonomisinin Benimsenme Sıklığı

Arafat Salih AYDINER¹

Başvuru Tarihi/Submitted: 22.06.2026 Kabul Tarihi/Accepted: 13.08.2026

Makale Türü/Article Type: Araştırma Makalesi/Research Article

Abstract

Artificial intelligence (AI) adoption is widely studied at the organizational level, yet much less is known about the specific algorithms organizations adopt and the reasons for these choices. This study investigates AI adoption among research-and-development (R&D) small and medium-sized enterprises (SMEs) and start-ups in Türkiye through a proposed expert-driven, learning-domain-based taxonomy comprising 28 algorithms grouped into seven AI families. Survey data were collected from 36 organizations affiliated with the Istanbul Chamber of Commerce. Reliability and validity were established, and adoption was examined through descriptive statistics and non-parametric Kruskal-Wallis and Mann-Whitney tests. At the algorithm level, Decision Trees, Neural Networks, Multilayer Perceptron, and Linear Regression were the most adopted, reflecting a preference for interpretable, structurally familiar methods, whereas Deep Q-Network, Policy Gradient, and Simultaneous Localization and Mapping were the least adopted. At the family level, Unsupervised Learning and Natural Language Processing ranked highest, while Reinforcement Learning and Autonomous Behavior recorded the lowest and most divergent adoption. Adoption also varied by sector—Financial/FinTech and Engineering/Defense showed the broadest portfolios and Healthcare and Commerce/e-Commerce the narrowest—with statistically significant cross-sector differences for Autonomous Behavior and Unsupervised Learning. Adoption range increased across organizational stages, peaking at post-incubation. The findings extend the Technology-Organization-Environment framework with diffusion of innovation and dynamic capability theory to the algorithm level and emphasize AI algorithms' knowledge as a target for SMEs' digital transformation.

Keywords: Artificial intelligence adoption, artificial intelligence taxonomy, artificial intelligence family, artificial intelligence algorithms, technology-organization-environment framework

JEL Code: M15, M13, O33

Öz

Yapay zekânın (YZ) kurumsal düzeyde benimsenmesi yaygın olarak incelenmiş olsa da, firmaların benimsediği spesifik algoritmalar ve bu seçimlerin nedenleri hakkında az bilgi bulunmaktadır. Bu çalışma, Türkiye'deki araştırma ve geliştirme (AR-GE) küçük ve orta ölçekli işletmeler (KOBİ'ler) ve yeni kurulan şirketler arasında YZ'nin benimsenmesini, yedi YZ ailesine gruplandırılmış 28 algoritmadan oluşan, uzman odaklı, öğrenme alanı tabanlı bir taksonomi önerisi aracılığıyla araştırmaktadır. Anket verileri İstanbul Ticaret Odası'na bağlı 36 kuruluşta toplanmıştır. Güvenilirlik ve geçerlilik sağlanmış ve benimsenme, tanımlayıcı istatistikler ve parametrik olmayan Kruskal-Wallis ve Mann-Whitney testleri ile incelenmiştir. Algoritma düzeyinde, Karar Ağaçları, Sinir Ağları, Çok Katmanlı Algılayıcı ve Doğrusal Regresyon en çok benimsenen algoritmalar olup, yorumlanabilir ve yapısal olarak tanınmış yöntemlere olan tercihi yansıtmaktadır. Buna karşılık, Derin Q-Ağı, Politika Gradyanı ve Eşzamanlı Konumlandırma ve Haritalama en az benimsenen algoritmalar olmuştur. Aile düzeyinde, Denetimsiz Öğrenme ve Doğal Dil İşleme en yüksek sıralarda yer alırken, Takviyeli Öğrenme ve Otonom Davranış en düşük ve en farklı benimsenme oranlarıyla sonuçlanmıştır. Benimsenme sektörleri göre de farklılık göstermektedir. Finans/FinTech ve Mühendislik/Savunma en geniş benimsenme portföyünü içerirken, Sağlık ve Ticaret/e-Ticaret en dar portföyü sunmaktadır. Otonom Davranış ve Denetimsiz Öğrenme istatistiksel olarak sektörler arası anlamlı farklılıklar göstermektedir. Benimsenme aralığı organizasyonel aşamalarda artarak kuluçka sonrası durumda zirveye ulaşmıştır. Bulgular, Teknoloji-Organizasyon-Çevre çerçevesini, yenilik yayılımı ve dinamik yetenek teorisiyle algoritma düzeyine getirmekte, hedef olarak KOBİ'lerin dijital dönüşümünde yapay zekâ algoritma bilgisinin önemini ortaya koymaktadır.

Anahtar Kelimeler: Yapay zekanın benimsenmesi, yapay zekanın taksonomisi, yapay zeka ailesi, yapay zeka algoritmaları, teknoloji-organizasyon-çevre çerçevesi

JEL Kodu: M15, M13, O33

Atıf/Citation: Aydın, A.S. (2026). Adoption frequencies of expert-driven learning-based AI Taxonomy among R&D SMEs and start-ups in Türkiye. *Anadolu Üniversitesi Sosyal Bilimler Dergisi*, 26(3), 1589-1614.

¹İstanbul Medeniyet Üniversitesi, Siyasal Bilgiler Fakültesi, İşletme Bölümü, Yönetim Bilişim Sistemleri Anabilim Dalı, Doktor Öğretim Üyesi, arafat.aydiner@medeniyet.edu.tr, ORCID: 0000-0002-1133-5995

Introduction

Artificial Intelligence (AI) has become a widely adopted technology across all different levels of life, with a range of industrial, intellectual, and social applications (Dwivedi et al., 2021). Business practitioners are applying AI tools individually, but organizations remain skeptical. It is predicted that AI will augment innovative solutions and cognitive capabilities in both businesses and human life (Dwivedi et al., 2021). These developments indicate that AI is creating a fast-changing competitive environment for small and medium enterprises (SMEs) that focus on research and development (R&D) and start-ups. These organizations strive to align their processes with AI capabilities while attempting to complete their digital transformation processes. However, AI adoption appears to have different characteristics in research and development (R&D)-oriented SMEs and start-ups than in large companies. In addition, the diffusion of AI is relatively low in SMEs and start-up organizations due to financial, infrastructural, and human capital constraints (OECD, 2025).

Most of the research indicates that AI cannot be considered a standalone technology. It is a broad field and comprises different technical clusters of algorithms with a range of categories that mimic human cognitive capability, process data, and handle complex tasks (Chowdhury et al., 2023; Lu, 2019). The most commonly considered categorizations are machine learning, deep learning, natural language processing, large language models, ensemble models, and robotic and control systems (Nagahisarchoghaei et al., 2023).

Despite the growing body of research on AI adoption, prior studies have largely examined whether organizations adopt AI, treating it as a single, undifferentiated technology. Thus, the algorithm-level perspective remains underdeveloped in the literature (AlSheibani et al., 2018; Chen, H. et al., 2021). R&D SMEs and start-ups that embed AI through application programming interfaces (APIs) or off-the-shelf tools often lack visibility into the specific algorithms powering those tools, which creates a black-box problem that undermines trust, accountability, and strategic alignment (Dwivedi et al., 2021; Y. Liu & Wang, 2026). Furthermore, existing AI taxonomies tend to operate at a conceptual or paradigm level, offering limited guidance for practitioners who need to select, implement, and compare specific algorithms in applied settings (Dutta, 2025). Therefore, there is a gap in the in-depth understanding of which AI taxonomies can be used to classify the algorithms adopted by R&D SMEs and start-ups. Likewise, variation in adoption by sector and organizational stage, as well as the patterns through the Technology-Organization-Environment (TOE) framework, Diffusion of Innovation (DOI) theory, and Dynamic Capability Theory (DCT) perspectives, has received limited research attention in current AI taxonomies.

To address these gaps, the study aims to investigate the research questions concerning adoption frequencies of the AI algorithms and families included in the proposed taxonomy and examine the adoption patterns in different organizational sectors and stages within the context of Turkish R&D SMEs and start-ups. The study adopts a quantitative survey design grounded in an AI taxonomy comprising seven algorithm families, namely Supervised Learning, Unsupervised Learning, Reinforcement Learning, Deep Learning, Natural Language Processing, Ensemble Learning, and Autonomous Behavior. The survey questionnaire was developed, validated with AI practitioners and academics, and administered to 36 professionals from R&D SMEs and start-ups. Organizational stages were classified as R&D, pre-incubation, incubation, and post-incubation, in line with Mungila Hillemane et al. (2019). Due to the small sample size, descriptive statistics and non-parametric analyses were applied.

The theoretical contribution of the research is to extend the TOE framework, DOI, and DCT to algorithm and family-level analysis, moving beyond aggregate AI adoption measures to examine which specific algorithms R&D SMEs and start-ups adopt. The study also provides an empirical foundation for the black-box concern in the AI adoption literature by demonstrating that algorithm knowledge operates as an implicit selection criterion among R&D SMEs and start-ups. Practically, the expert-driven learning-based AI taxonomy developed here offers a structured instrument for entrepreneurs, accelerators, and policymakers to guide algorithm-level capability building.

The remainder of the study presents the theoretical background in the next section. The following section outlines the research methodology with the research questions. The next section includes data analysis results. The last section covers the discussion, conclusion, and future research perspectives.

Literature Review

The background of AI is complex because it is grounded in mathematical algorithms and models. Although the outcomes are often appreciated, the complexity of AI models and algorithms often leads to skepticism regarding their processes, operations, and functions. This uncertainty creates a black box perception around algorithmic tasks (Long & Magerko, 2020), and detailed discussions were conducted in the literature review.

AI in R&D SMEs and Start-ups

AI enables the automation and augmentation of many tasks typically performed by human intelligence. In order to perform these tasks, AI serves as a system that can accurately analyze data and learn from it to accomplish specific objectives (AlSheibani et al., 2018; Ayinaddis, 2025). SMEs and start-ups have the ambition to gain these AI capabilities to achieve their objectives. However, they have limited resources, knowledge gaps, infrastructure constraints, and cultural challenges that distinguish them from large organizations (AlSheibani et al., 2018; Zebec & Indihar Štemberger, 2020). Therefore, identifying specific algorithms and models behind AI is essential for selecting solutions suited to R&D SMEs and start-ups.

The prior studies define AI as digital technologies that mimic or augment human cognitive capabilities to perform complex, structured, or unstructured tasks autonomously or semi-autonomously (AlSheibani et al., 2018; Ayinaddis, 2025; Y. Liu & Wang, 2026). AI is expected to improve decision-making and productivity by enhancing cognitive performance, often conceptualized as an “intelligent agent” (Hansen et al., 2024; Mikalef et al., 2022; Radhakrishnan & Chattopadhyay, 2020).

The implementation of AI fosters innovation, productivity, and resilience by playing a transformative role (OECD, 2025; Uren & Edwards, 2023). Accordingly, R&D-oriented SMEs and start-ups utilize AI to build strategic capabilities and improve performance. AI supports data-driven decision-making and enhances functionalities, which can lead to productivity gains. Furthermore, AI adoption also supports IT resource productivity (Chen, H. et al., 2021; Hansen et al., 2024). Key characteristics of AI, like speed, scale, granularity, and learning, open up significant opportunities for innovation (Zebec & Indihar Štemberger, 2020). The literature therefore suggests that AI becomes a critical component in enabling R&D SMEs and start-ups to sense opportunities, seize them, and transform themselves in a dynamic environment (Long & Magerko, 2020).

R&D SMEs and start-ups have a higher tendency to adopt AI technologies by utilizing AI APIs and off-the-shelf AI models to overcome resource constraints (OECD, 2025). Utilizing AI APIs or off-the-shelf AI models may increase adoption, but the output of these models or algorithms embedded in AI tools may not align with organizations' specific context. A major issue in implementing AI tools is whether their outputs can be trusted. Therefore, the outputs of AI tools need to be checked constantly. Also, inaccurate information, harmful content, and legal or copyright issues are important concerns when adopting off-the-shelf AI tools (Y. Liu & Wang, 2026).

AI Adoption from the Perspective of Diffusion of Innovation (DOI) and Dynamic Capability Theory (DCT), and Technology-Organization-Environment (TOE) Framework

Theoretical perspectives provide a useful structure for understanding the complexity of AI adoption. In particular, the TOE framework offers a multidimensional view of adoption, while DOI explains adoption through the perceived characteristics of innovation.

The technological dimension of the TOE framework emphasizes the relative advantage of AI adoption if the perceived result is better than existing operations and processes. When R&D SMEs and start-ups perceive clear performance benefits, they are more likely to scale up AI implementation. Relative advantage promotes the diffusion of AI across all sectors (AlSheibani et al., 2018; Chen, H. et al., 2021). Compatibility with existing technological infrastructure and alignment with organizational values are strong predictors of AI adoption. Technological readiness is another DOI-related dimension in which R&D SMEs and start-ups possess the necessary IT infrastructure to align complex AI algorithms and models (AlSheibani et al., 2018; Ayinaddis, 2025; Chen, H. et al., 2021).

Internal organizational dynamics are also an enabler or deterrent factor for AI adoption. Top-level managers' commitment to digital transformation is a key driver of AI adoption in R&D SMEs and start-ups (Ayinaddis, 2025; Chen, J. et al., 2025). Financial readiness for costly AI technologies is a major barrier for R&D SMEs and start-ups. Financial constraints negatively affect the availability of employee skills and competencies (Ayinaddis, 2025; Mikalef et al., 2022). However, smaller organizations are more flexible and agile than larger ones. These capabilities give R&D SMEs and start-ups an advantage in adopting and diffusing AI algorithms easily and quickly (AlSheibani et al., 2018). Organizational size is therefore an important determinant of AI adoption.

Environmental factors also influence the direction of technological investment. Therefore, AI diffusion is affected by external stakeholders' positions on AI adoption as well. Competition among SMEs is often intense. This creates pressure on SMEs to invest in new technologies, especially data-driven ones. A data-driven environment generates large volumes of rich data. This large volume of rich data is the basis of big data for AI and creates pressure for R&D SMEs and start-ups to adopt AI (AlSheibani et al., 2018; Ayinaddis, 2025; Chen, H. et al., 2021). Ethical guidelines, data privacy laws, and security standards are also critical environmental factors shaping the AI adoption strategies for R&D SMEs and start-ups (Chen, H. et al., 2021; Mikalef et al., 2022).

Dynamic capability theory explains the development of the ability to select, orchestrate, and leverage AI resources (Mikalef & Gupta, 2021). From the perspective of DCT, understanding AI algorithms and models becomes a critical capability for R&D SMEs and start-ups to select, implement, and transform AI resources effectively. Thus, the main research question examines how the adoption frequency of AI algorithms in R&D SMEs and start-ups can be interpreted through the TOE framework. The main objective of the study is to understand the underlying logic of AI algorithms to clarify how organizations direct their AI-related resources.

AI Algorithms

The core components of AI systems are algorithms and models. AI algorithms are computational procedures that enable machines to learn patterns from data (Fabregat-Hernández et al., 2023). AI models are trained computational structures resulting from applying these algorithms. However, the terms "algorithm" and "model" are used interchangeably in the field. They represent distinct yet interconnected concepts. Together, they help to explain how the fundamental notion of an AI system functions (Du-Harpur et al., 2020). The pervasive adoption of AI technologies is driven by several factors. Increasing computational power, particularly by graphical processing units (GPUs), advances the AI technological infrastructure. The exponential growth of datasets is another key factor in operating effectively. In addition, theoretical improvements in machine learning methodologies accelerate the development of AI technologies (Du-Harpur et al., 2020). These developments in AI systems enable significant performance enhancements across a wide range of applications, tasks, and domains (Chen, J. et al., 2025; Mikalef & Gupta, 2021; Zebec & Indihar Štemberger, 2020).

Algorithms are characterized as automated, highly flexible, and computationally intensive approaches compared with traditional statistical methods (Mikalef & Gupta, 2021). Three key characteristics help to identify algorithms. The first is learning rules, adjusting weights, or model parameters. The second is that algorithms learn from data to make predictions or decisions in every possible scenario. The last is to recognize and extract patterns from datasets (OECD, 2025; Eckhardt et al., 2023; Mikalef & Gupta, 2021). The algorithm defines how learning occurs, whereas the models represent what has been learned through that process. In practical terms, practitioners and researchers choose algorithms based on the nature of their problems and the characteristics of the data. That algorithm is then applied to training data, resulting in a model with specific learned parameters. Later, this model can be deployed to make predictions on new data (Fabregat-Hernández et al., 2023; Long & Magerko, 2020).

Understanding AI algorithms

R&D SMEs and start-ups need to move beyond AI adoption towards AI capability. From a DCT perspective, AI capability enables organizations to select, orchestrate, and leverage AI-specific resources, whereas adoption alone does not provide a sufficient basis for managing the necessary resources to transform organizational value. Therefore, the transition from AI adoption towards AI capability requires synchronization and planning with a top-down approach (Mikalef et al., 2022).

There is always a challenge in identifying what data needs to be captured, used, and trained for specific algorithms within a given domain. Algorithm knowledge is critical for overcoming these challenges because it helps to recognize the need for good-quality data to train AI models (Dwivedi et al., 2021). Understanding the underlying algorithm strengthens both AI adoption and AI capability by allowing businesses to match solutions to their specific needs (Hossain et al., 2022). Cognitive and knowledge-based AI capability can turn small organizations into AI explorers and champions (OECD, 2025). Reliance on well-known algorithms due to existing computational infrastructure leads organizations to disregard niche algorithms. Distinguishing between commonly used and less implemented algorithms creates a competitive edge by enabling R&D SMEs and start-ups to explore niche models (Dwivedi et al., 2021). One of the objectives of this research is to analyze and compare the adoption of AI algorithms among R&D SMEs and start-ups to distinguish these differences.

The data required for R&D SMEs and start-ups to train their own AI systems is likely to increase internal data management capacity and security risks. Greater exposure to digital security risks increases the need to understand AI algorithms and train them securely (Y. Liu & Wang, 2026). From a DOI perspective, this approach can lead to innovative solutions and help differentiate R&D SMEs and start-ups from their competitors.

AI systems function like a black box, making it difficult to understand the reasons behind their results. AI algorithms can develop biases from training data, which may lead to harmful, unconventional, and unethical outputs. The systems that learn autonomously can have unpredictable consequences as well. The key step toward opening the black box and addressing this lack of explainability is to understand AI algorithms (Dwivedi et al., 2021). Therefore, this study focuses on the level of AI algorithm knowledge among R&D SMEs and start-ups, together with their adoption frequencies, in order to investigate the adoption pattern across different business domains and organizational stages to open the black box.

AI algorithm taxonomy

Capabilities, functionalities, techniques, deployment environment, purpose, and application domains are common dimensions used in AI taxonomy design (Dutta, 2025). The AI taxonomy explicitly relates algorithms to paradigms, mathematical foundations, and typical use cases described in prior literature (Alekseev & Strobel, 2026; Dutta, 2025; Gill et al., 2025; Raiaan et al., 2024; Talbi, 2020; Wu et al., 2023). Another approach to AI taxonomy is to classify AI according to its constituent algorithms. Gama and Brazdil (1995) characterize a broad set of algorithms used for classification. Their framework implicitly partitions algorithms into families (J. Gama & Brazdil, 1995). In this study, the AI taxonomy was designed around technical dimensions in order to better understand R&D SMEs and start-ups' approach to AI adoption. The study's AI taxonomy is more closely aligned with the partitioning algorithm framework proposed by Gama and Brazdil (1995) and reflects a technically based, practically oriented engineering approach (Dutta, 2025) which supports the objective of this research.

The main aim of the proposed AI taxonomy is to provide a concise map of AI algorithms, categorized by training paradigm and supporting techniques, in order to analyze adoption among R&D SMEs and start-ups. Many taxonomies are at the conceptual or paradigm level. This taxonomy was designed at the algorithm level. Linking algorithm-level awareness to the application domains, the taxonomy gives practitioners a broader understanding of which AI algorithm families are relevant for implementation. The study's AI taxonomy was developed through an expert-driven approach, supported by theoretical perspectives from the literature and focused on the learning paradigm (Alekseev & Strobel, 2026; Dutta, 2025; J. Gama & Brazdil, 1995; Gill et al., 2025; Talbi, 2020). Consultation with three AI practitioners from academia and industry during the taxonomy design process helped strengthen both its theoretical ground and practical relevance, resulting in an expert-driven perspective for applied needs. The taxonomy also helps explain how R&D SMEs and start-ups implement algorithms and how these adoption patterns can be interpreted through the TOE framework together with DOI and DCT. The resulting expert-driven learning-domain-based taxonomy is presented in Table 1.

Table 1

Expert-Driven Learning-Domain-Based Taxonomy

Supervised Learning	Unsupervised Learning	Reinforcement Learning	Deep Learning	Natural Language Processing	Ensemble Learning	Autonomous Behavior
Linear Regression	k-Means Clustering	Q-Learning	Neural Network	Word Embeddings	Boosting-AdaBoost	Simultaneous Localization and Mapping
Logistic Regression	Autoencoders	Deep Q-Network	Convolutional Neural Network	Bidirectional Encoder Representations	Stacking	Kalman Filter
Support Vector Machines		Policy Gradient Methods	Recurrent Neural Network	Generative Pre-Trained Transformers		Model Predictive Control
Naïve Bayes			Graph Neural Network			Robotic Process Automation
Decision Trees			Transformer Models			
Bayesian Networks			Multilayer Perceptron			
Random Forest			Generative Adversarial Network			

Supervised learning (SL): Supervised learning is a method that learns by mapping inputs to an output. Training data are labeled, meaning that the correct output is already known for each example. These labeled examples are used to train a model to predict or classify outcomes for new data as accurately as possible (Jiang et al., 2020).

The method is applied to historical data with input features and known outcomes in order to predict new cases. Typical applications include predicting continuous quantities, such as future sales or disease risk scores, and classifying cases (Jiang et al., 2020; Valkenborg et al., 2023). The algorithms that are listed under supervised learning are all trained on labeled data. Their objective is to learn a function that predicts targets for new examples with minimal error in regression tasks or maximum accuracy in classification (Jiang et al., 2020; Mohri et al., 2018).

Unsupervised learning (UL): Unsupervised learning analyzes unlabeled data to discover patterns, structures, or groupings without access to target outputs (Abukmeil et al., 2022). The purpose of unsupervised learning methods is to uncover data distributions, learn underlying structures, remove redundancies, and reduce dimensionality in high-dimensional datasets (Abukmeil et al., 2022; Eckhardt et al., 2023). Common applications of unsupervised learning include clustering, dimensionality reduction, anomaly detection, and exploratory data analysis (Abukmeil et al., 2022; Mohri et al., 2018). The algorithms in this category operate on unlabeled datasets and optimize internal objectives. Thus, these algorithms are classified under the unsupervised learning category in the study's AI taxonomy.

Reinforcement learning (RL): Reinforcement learning is a paradigm in which autonomous agents learn to make sequential decisions by interacting with an environment. These agents learn through trial-and-error interactions and receive rewards or penalties based on their actions. The primary objective is to develop an optimal behavioral strategy. Reinforcement learning is a framework that is modeled as a Markov Decision Process (MDP) (Y. T. Liu et al., 2020; Shakya et al., 2023). RL is typically applied in domains where sequential decision-making is too complex or costly to handle with conventional approaches, such as gaming, healthcare, finance, and energy management (Shakya et al., 2023). All methods classified under the RL family learn behavioral strategies directly from interaction experience (Shakya et al., 2023).

Deep learning (DL): Deep learning (DL) is a computational model composed of multiple layers that gradually extract higher-level features from raw input data (Gheisari et al., 2023). The term “Deep” refers to the number of processing layers through which data passes, which allows DL methods to learn complex concepts by building them from simple ones. This layered structure makes DL particularly well suited to processing large volumes of unstructured data (Ahmed et al., 2023).

The algorithms within the DL family rely on a layered network architecture. Feature representations are learned automatically from data through multiple levels of abstraction. This learning process depends on non-linear transformations and backpropagation (Ahmed et al., 2023; Rana et al., 2018).

Natural language processing (NLP): NLP handles language by analyzing, understanding, and generating language in a human-like manner. These techniques enable the processing of textual data. NLP usually requires text for raw input. Words and documents are represented as numeric vectors that preserve semantic and syntactic information (Raiaan et al., 2024; Wadud et al., 2022). Large language models (LLMs) are advanced NLP models. LLMs are based on billions of parameters and are trained on a large collection of unlabeled text using self-supervised objectives (Raiaan et al., 2024; Shao et al., 2024). Therefore, NLP is used to convert textual or linguistic data into structured information or to support decision-making (Raiaan et al., 2024; Shao et al., 2024).

The algorithms within the NLP family share common characteristics. They all depend on large amounts of unlabeled text. These algorithms are language representation models that organize text into numerical vectors and optimize language-model objectives (Devlin et al., 2019; Raiaan et al., 2024; Shao et al., 2024).

Ensemble learning (EL): Ensemble learning (EL) approaches aggregate two or more learners for training, then combine their predictions with a predefined rule to produce a single result. This method cancels out individual errors (Mienye & Sun, 2022). EL is usually implemented when a single model cannot simultaneously achieve low bias and low variance. When data is noisy, high-dimensional, or imbalanced, EL is the preferred method (Mienye & Sun, 2022). AdaBoost is a sequential ensemble, while stacking is a parallel ensemble. Both algorithms produce the best outputs for reducing bias and variance (Mienye & Sun, 2022; Schapire, 2013).

Autonomous behavior (AB): Autonomy is defined as the capability of a system to perform intended behaviors, tasks, and processes based on its current state and sensing without human intervention (Prestes et al., 2013). Fully autonomous behavior adapts itself to operational and environmental conditions to complete specific tasks. Agents performing these tasks have the cognitive capacity to decide independently and instantaneously (Fiorini et al., 2015; Prestes et al., 2013). Sensing, state estimation, planning, decision-making, and task execution are the behaviors through which these algorithms operate to achieve non-human cognitive capacity (Aydiner et al., 2023; Bai et al., 2023; Ding et al., 2018; Pramod, 2022).

AI Algorithms Taxonomy-Based Adoption Approach

The diffusion of AI algorithms, with their varying capabilities, creates distinct adoption patterns among R&D SMEs and start-ups. The expert-driven learning-domain-based taxonomy developed in this study provides a framework for understanding which algorithms are frequently adopted and implemented across different organizational sectors and stages.

Accordingly, the study addresses the following research questions:

Q1: Which AI algorithms are most frequently adopted by R&D SMEs and start-ups?

Q2: Which AI algorithm families are most frequently adopted across different organizational sectors among R&D SMEs and start-ups?

Q3: Which AI algorithm families are most frequently adopted across different organizational stages among R&D SMEs and start-ups?

This research aims to identify AI algorithms' adoption patterns among R&D SMEs and start-ups in order to understand innovation diffusion and the enhancement of dynamic capabilities.

Research Methodology

Survey Settings

The study adopts a quantitative research design based on survey methodology, with guidance from prior literature (Dillman, 2007). The survey questionnaire was developed using a 5-point Likert scale in the English language. Since the research aimed to target Turkish R&D SMEs and start-ups, the survey was subsequently translated into the Turkish language to facilitate participation among Turkish-speaking respondents. The survey was then backtranslated into English in order to ensure linguistic accuracy and integrity. Both Turkish- and English-language experts evaluated the questionnaire. The final version of the survey was approved, as the back-translated version did not reveal any major semantic differences or contradictions.

The survey instrument was prepared through a multi-stage process. The existing literature helped to include AI algorithm families and their member algorithms in the development of an initial AI taxonomy proposal (Dutta, 2025; F. Gama & Magistretti, 2025; J. Gama & Brazdil, 1995). The questionnaire also captured participants' sector affiliations and organizational stages, which were classified as research and development (R&D), pre-incubation, incubation, and post-incubation, in line with the study by Mungila Hillemane et al. (2019).

The content validity of the survey measurement was established systematically, as suggested by Hair et al. (2007). First, in-depth interviews were conducted with AI practitioners, developers, and managers working in R&D SMEs and start-ups in order to validate the proposed AI taxonomy. Subsequently, the questionnaire was revised according to the feedback received from the subject-matter experts. Additional feedback was received from three academics who are in the field of AI and Management Information Systems. Consequently, the final version of the survey was developed and consisted of 32 questions.

Before data collection began, ethical approval was obtained from the Social Science Ethics Committee of Istanbul Medeniyet University. All procedures adhered to the ethical standards that the committee required. Informed consent was prepared at the beginning of the survey, which included information on data confidentiality and voluntary participation. The survey was prepared using a digital application called SurveyMonkey and disseminated through e-mails and LinkedIn accounts to the relevant audience.

Study Sample and Data Collection

The study relies on a non-probability convenience sample of professionals actively engaged in AI-related roles, such as AI developers, managers, and practitioners (Etikan et al., 2016). Participants were selected based on direct involvement with AI systems within R&D SMEs and start-ups at the pre-incubation, incubation, and post-incubation stages, all of which operate in Türkiye and are members of the Istanbul Chamber of Commerce. The content of the study requires advanced knowledge of AI technologies and the capability to adopt them; thus, the volume of participants from entrepreneurial and R&D companies was limited, despite the use of the LinkedIn application. A total of 38 R&D SMEs and start-ups were contacted. During the data pre-processing stage, two respondent companies were eliminated due to a lack of information. The final number of valid responses was 36. The sample should be understood as context-specific to Istanbul-based R&D SMEs and start-ups rather than as representative of the broader population of Turkish R&D SMEs, and self-selection of AI-engaged respondents cannot be ruled out.

Data Analysis and Results

Due to the small sample size constraint ($N=36$), descriptive statistics and non-parametric analyses were performed throughout the research using Python coding with Pandas and NumPy packages. Descriptive statistics provided the median and interquartile range (IQR) to measure central tendency and dispersion for ordinal data (Revelle & Condon, 2019). Sample characteristics of the data were calculated to show the distribution of participants (Table 2), roles (Table 3), organizational stages (Table 4), and whether the participants are established in a Technopark (Table 5). Given the limited and geographically concentrated convenience sample, the findings reported below

are not statistically generalizable to the broader population of Turkish R&D SMEs and start-ups. They provide preliminary, context-specific insights into AI taxonomy adoption within this setting. Although 36 of 38 contacted organizations responded (94.7%), the small contact frame means the high response rate does not offset potential coverage and self-selection biases.

Table 2

Distribution of Participants by Sector

SECTOR	N	Percentage (%)	Cumulative (%)
Commerce/E-Commerce	3	8.3%	8.3%
Engineering/Defense	6	16.7%	25.0%
Financial/Fintech	5	13.9%	38.9%
Healthcare	2	5.6%	44.4%
IT/Software	14	38.9%	83.3%
Service	6	16.7%	100%
Total	36	100%	

Table 3

Distribution of Participants by Role

ROLES	N	Percentage (%)	Cumulative (%)
Entrepreneur	18	50.0%	50.0%
Executive Manager	3	8.3%	58.3%
Operational Manager	11	30.6%	88.9%
Others	4	11.1%	100%
Total	36	100%	

Table 4

Distribution of Participants by Organizational Stages

STAGES	N	%	Cumulative N	Cumulative (%)
R&D	24	66.7%	24	66.7%
Pre-Incubation	4	11.1%	28	77.8%
Incubation	5	13.9%	33	91.7%
Post-Incubation	3	8.3%	36	100.0%
Total	36	100%		

Table 5

Distribution of Participants by Technopark

TECHNOPARK	N	Percentage (%)	Cumulative (%)
No	26	72.2%	72.2%
Yes	10	27.8%	100.0%
Total	36	100%	

Note: Technopark status refers to whether the SMEs/start-ups are registered within a technology park.

Reliability and Validity

The reliability coefficient, which is Cronbach's alpha, was measured for each AI family in the taxonomy to assess the study's reliability. Six of the seven AI families' Cronbach's alpha exceeded the conventional threshold of $\alpha \geq 0.70$ (Nunnally, 1978). When the number of items was limited, and the Cronbach's alpha value fell below the threshold, McDonald's omega was checked for the reliability of the measurement. The Unsupervised Learning (UNSL) family fell marginally below it ($\alpha = 0.67$), an expected artifact of its two-item composition, because alpha is a lower-bound estimate that assumes tau-equivalence and is downward-biased for short scales (Cortina, 1993). McDonald's omega, which relaxes the tau-equivalence assumption and is therefore the preferred reliability estimator irrespective of scale length (Hayes & Coutts, 2020), exceeded 0.80 for every family ($\omega = 0.85\text{--}0.94$), indicating good reliability (McDonald, 2011). The acceptable threshold value for alpha redundancy was chosen as 0.95 (Tavakol & Dennick, 2011), thus no potential redundancy risk was found. Composite reliability (CR) and average variance extracted (AVE) are additionally reported in Table 6 for exploratory reference only. Both indices are functions of standardized factor loadings, and loading estimates are unstable at small sample sizes (Hair et al., 2019; MacCallum et al., 1999). With $N = 36$, the present sample does not meet these conditions, so CR and AVE values, although all exceeded the conventional benchmarks of $CR \geq 0.70$ and $AVE \geq 0.50$ (Fornell & Larcker, 1981), must not be read as confirmatory evidence of convergent validity. They are retained for transparency and as preliminary benchmarks, noting that factor-analytic estimates from small samples can be informative when communalities are high and the structure is simple (de Winter et al., 2009), and that ω and CR coincide under the congeneric model estimated here (Cho, 2016), as reflected in Table 6. Consequently, this study is positioned as an exploratory study of the proposed taxonomy.

Table 6

Reliability and Descriptive Measurements of AI Taxonomy

TAXONOMY FAMILY	K	N	Median	IQR	Mean	SD	Cronbach's α	ω	CR	AVE
Supervised Learning (SL)	7	36	2.643	1.03	2.611	1.030	0.9047	0.9244	0.9244	0.6381
Unsupervised Learning (UNSL)	2	36	3	1.197	2.875	1.197	0.6697	0.8677	0.8677	0.7663
Reinforcement Learning (RL)	3	36	2	1.197	2.167	1.197	0.8952	0.9406	0.9406	0.841
Deep Learning (DL)	7	36	2.857	1.003	2.786	1.003	0.8568	0.8863	0.8863	0.5294
Natural Language Processing (NLP)	3	36	2.833	1.15	2.750	1.150	0.7542	0.8582	0.8582	0.6691
Ensemble Learning (EL)	2	36	2.5	1.259	2.500	1.259	0.8293	0.9354	0.9354	0.8786
Autonomous Behavior (AB)	4	36	2.125	0.984	2.167	0.984	0.7627	0.8517	0.8517	0.5955

Notes: K = number of constituent algorithms per family, IQR = Interquartile range, SD = Standard deviation, ω = McDonald's omega, CR = Composite reliability, AVE = Average variance extracted.

AI Algorithms and Families' Adoption Frequencies

One of the study's research questions is to understand the most commonly adopted algorithms in R&D SMEs and start-up organizations. Hence, a descriptive frequency analysis of the adoption of 28 algorithms across seven algorithm families was conducted based on the responses from 36 participants. The original data collected on a five-point Likert scale were recoded into a binary variable (original value 1 = Not Adopted, coded as 0; original values 2 to 5 coded as 1 = Adopted). Because the algorithm families contain unequal numbers of items, naïve pooled frequency ratios would generate a bias that inflates the apparent adoption of larger families. This bias was corrected by calculating the proportion of algorithms within a family that were used ($p_i = \text{used algorithms} / K = \text{number of items in a family}$) and then averaging these proportions across respondents (Crocker & Algina, 1986; DeVellis & Thorpe, 2022).

Algorithm-level adoption frequency

Algorithm-level adoption frequency analysis indicated that the most adopted algorithm was Decision Trees ($f = 31$; 86.11%), consistent with their long-established interpretability and accessibility (Breiman, 2001; Hastie et al., 2009), which explains the development of decision-making applications with non-linear relationships (Jiang et al., 2020). Neural Networks ($f = 30$; 83.33%) and Multilayer Perceptron (MLP) ($f = 29$; 80.56%) ranked second and third, reflecting that foundational Deep Learning architectures are commonly adopted by R&D SMEs and start-ups. Linear Regression ($f = 29$; 80.56%) tied for third, underscoring the enduring relevance of classical statistical methods in AI-adjacent practices. These are the top four adopted algorithms that are implemented by R&D SMEs and start-up organizations.

Analysis revealed that GPT, Word2Vec, and Autoencoders were at the same level of adoption ($f = 28$; 77.78%), indicating broad adoption of both generative and representational approaches. Transformer Models, Recurrent Neural Networks, and Convolutional Neural Networks were at the same adoption frequency and in the same family, which is Deep Learning ($f = 27$; 75.00%). This showed that unstructured, high-volume data plays a role in the adoption of these algorithms for the respective organizations. Graph Neural Networks and k-Means Clustering displayed the same adoption frequency, although they belong to different families, namely Deep Learning and Unsupervised Learning ($f = 26$; 72.22%). A group of algorithms (Boosting, BERT, Stacking, SVM, Random Forest - $f = 25$; 69.44%) stands at the same level of adoption and seems less popular to implement. Logistic Regression is one of the least adopted classical algorithms ($f = 24$; 66.67%), as the dichotomous type of approach is less common among the participating organizations. The number of adoptions decreased for Naïve Bayes, Bayesian Networks, Q-Learning, and Kalman Filter ($f = 22$; 61.11%) algorithms, most of which are in the Deep Learning family, as well as Reinforcement Learning and Autonomous Behavior families. Robotic Process Automation (RPA) ($f = 20$; 55.56%), Generative Adversarial Networks (GAN), and Model Predictive Control (MPC) ($f = 19$; 52.78%) adoptions were at a low level; however, their frequencies were still above the average. Thus, these algorithms are also practically considered for R&D SMEs and start-ups' developed applications and products. Algorithms with adoption rates between 50.00% and 80.56% were at the mid-level of interest for R&D and start-up organizations. The analysis suggests that organizations adopt these algorithms occasionally, as needed.

The least adopted algorithms, with frequencies below 19, are Deep Q-Network and Policy Gradient ($f = 18$; 50.00%), and Simultaneous Localization and Mapping (SLAM) ($f = 17$; 47.22%). All frequency details of each algorithm are shown in Table 7.

Table 7

AI Algorithm and Families' Adoption Frequencies

RANK	ALGORITHM	FAMILY	N	f Adopted	f Not Adopted	Adopted (%)	Not Adopted (%)
1	Decision Trees	Supervised Learning	36	31	5	86.11%	13.89%
2	Neural Networks	Deep Learning	36	30	6	83.33%	16.67%
3	Multi-Layer Perceptron (MLP)	Deep Learning	36	29	7	80.56%	19.44%
4	Linear Regression	Supervised Learning	36	29	7	80.56%	19.44%
5	Generative Pre-Trained Transformer (GPT)	NLP / LLM	36	28	8	77.78%	22.22%
6	Word2Vec	NLP / LLM	36	28	8	77.78%	22.22%
7	Autoencoders	Unsupervised Learning	36	28	8	77.78%	22.22%
8	Transformer Models	Deep Learning	36	27	9	75.00%	25.00%
9	Recurrent Neural Networks (RNN)	Deep Learning	36	27	9	75.00%	25.00%

10	Convolutional Neural Networks (CNN)	Deep Learning	36	27	9	75.00%	25.00%
11	Graph Neural Networks (GNN)	Deep Learning	36	26	10	72.22%	27.78%
12	k-Means Clustering	Unsupervised Learning	36	26	10	72.22%	27.78%
13	Boosting (AdaBoost)	Ensemble Learning	36	25	11	69.44%	30.56%
14	Bidirectional Encoder Representation (BERT)	NLP / LLM	36	25	11	69.44%	30.56%
15	Stacking	Ensemble Learning	36	25	11	69.44%	30.56%
16	Support Vector Machines (SVM)	Supervised Learning	36	25	11	69.44%	30.56%
17	Random Forest	Supervised Learning	36	25	11	69.44%	30.56%
18	Logistic Regression	Supervised Learning	36	24	12	66.67%	33.33%
19	Naïve Bayes	Supervised Learning	36	22	14	61.11%	38.89%
20	Bayesian Networks	Supervised Learning	36	22	14	61.11%	38.89%
21	Q-Learning	Reinforcement Learning	36	22	14	61.11%	38.89%
22	Kalman Filter	Autonomous Behavior	36	22	14	61.11%	38.89%
23	Robotic Process Automation (RPA)	Autonomous Behavior	36	20	16	55.56%	44.44%
24	Generative Adversarial Networks (GAN)	Deep Learning	36	19	17	52.78%	47.22%
25	Model Predictive Control (MPC)	Autonomous Behavior	36	19	17	52.78%	47.22%
26	Deep Q-Network	Reinforcement Learning	36	18	18	50.00%	50.00%
27	Policy Gradient	Reinforcement Learning	36	18	18	50.00%	50.00%
28	Simultaneous Localization and Mapping (SLAM)	Autonomous Behavior	36	17	19	47.22%	52.78%

Note: **f Adopted** = absolute frequency of Adopted (1) responses; **f Not Adopted** = absolute frequency of Not Adopted (0) responses.

Family-level adoption frequency

Family-level adoption frequency is another approach for organizations to assess their DOI technological readiness. Unsupervised Learning (Mean % = 75.00%; Median % = 100%; Standard Deviation - SD % = 38.73%) and NLP (Mean % = 75.00%; Median % = 100%; SD % = 35.97%) jointly ranked highest in adoption. Despite both families having high mean adoption rates, their standard deviations revealed that a significant minority of respondents did not engage with either family. Specifically, 16.67% of respondents used no Unsupervised Learning algorithms, and 11.11% used no NLP algorithms. The high medians (100%) indicate that most respondents used all algorithms within these families, leading to a divergent distribution.

Deep Learning adoption placed third (Mean % = 73.41%; Median % = 85.71%; SD % = 33.66%) and exhibited the lowest standard deviation of all families, indicating a relatively consistent adoption range across respondents. Notably, 47.22% of respondents used some but not all Deep Learning algorithms, suggesting that R&D SMEs and start-ups are selective within this large family when adopting. Supervised Learning (Mean % = 70.63%; Median % = 85.71%; SD % = 36.29%) showed a similarly broad partial adoption pattern, with 47.22% of respondents in the category.

Ensemble Learning (Mean % = 69.44%; SD % = 45.16%) presented the most differentiated distribution of any family, with 94.4% of respondents using either none (27.78%) or all (66.67%) of its two algorithms, and only 5.56% at the intermediate level.

Autonomous Behavior (Mean % = 54.17%; SD % = 39.42%) and Reinforcement Learning (Mean % = 53.70%;

SD % = 45.97%) recorded the lowest adoption rates. Reinforcement Learning had the highest family-level SD (45.97%) and the largest proportion of complete non-adopters (36.11%), indicating that this family is characterized by a sharp specialist/non-specialist divide: 44.44% of respondents adopted all three RL algorithms, while 36.11% adopted none. All the detailed rankings for AI family-level adoption are shown in Table 8.

Table 8

AI Family-Level Adoption Frequencies

RANK	FAMILY	K	N	Mean Adopted (%)	Median Adopted (%)	SD (%)	f Adopted None (%)	f Adopted Some (%)	f Adopted All (%)
1	Unsupervised Learning	2	36	75.00%	100.00%	38.73%	6 (16.67%)	6 (16.67%)	24 (66.67%)
2	NLP	3	36	75.00%	100.00%	35.97%	4 (11.11%)	10 (27.78%)	22 (61.11%)
3	Deep Learning	7	36	73.41%	85.71%	33.66%	3 (8.33%)	17 (47.22%)	16 (44.44%)
4	Supervised Learning	7	36	70.63%	85.71%	36.29%	2 (5.56%)	17 (47.22%)	17 (47.22%)
5	Ensemble Learning	2	36	69.44%	100.00%	45.16%	10 (27.78%)	2 (5.56%)	24 (66.67%)
6	Autonomous Behavior	4	36	54.17%	50.00%	39.42%	8 (22.22%)	17 (47.22%)	11 (30.56%)
7	Reinforcement Learning	3	36	53.70%	66.67%	45.97%	13 (36.11%)	7 (19.44%)	16 (44.44%)

Note: K = number of constituent algorithms per family. **Mean % Adopted** = bias-corrected mean of per-respondent proportions $p_i \times 100$. **f Adopted None** = respondents who used 0 of K algorithms, **f Adopted Some** = respondents who used 1 to K-1 algorithms, **f Adopted All** = respondents who used all K algorithms.

Family-level adoption frequency in different organizational sectors and stages

When comparing adoption across families, the number of items varies. In order to prevent bias, proportional normalization was implemented in the context of technology (Venkatesh et al., 2003). Respondents reported adoption of 28 AI algorithms, each assigned to one of seven families (as shown earlier in Table 1). Each family is classified by sector and organizational stages (Tables 2 & 4).

Organizational sectors: Across the full sample, mean normalized adoption scores were ranked across the seven AI families and sectors (Table 9). The relatively high ranking of Unsupervised Learning (75.0%) showed widespread deployment of member algorithms across diverse task contexts. NLP sample mean result (75.0%) displayed the broad applicability of language models across all sectors except healthcare. Financial/FinTech and Engineering/Defense exhibited the broadest adoption portfolios across all seven families, with adoption scores above 70%. Healthcare showed dramatically lower adoption across all non-deep-learning families, with 0 scores for Unsupervised Learning, Ensemble Learning, and Reinforcement Learning. Commerce/e-Commerce similarly underperformed in Autonomous Behavior (0.0%) and Reinforcement Learning (11.1%), consistent with the predominantly digital, non-physical robotic operational context of these organizations.

Table 9

Normalized AI Family Adoption by Organizational Sector

FAMILY	Service N=6	Healthcare N=2	Commerce N=3	Fintech N=5	Eng/Def N=6	IT/SW N=14	Sample Mean
Supervised Learning	75.0%	8.3%	55.6%	90.0%	88.9%	66.7%	70.8%
Unsupervised Learning	66.7%	0.0%	50.0%	100.0%	91.7%	78.6%	75.0%
Ensemble Learning	61.1%	0.0%	33.3%	93.3%	88.9%	73.8%	69.4%
Deep Learning	66.7%	35.7%	57.1%	94.3%	85.7%	72.4%	73.4%

NLP	77.8%	16.7%	55.6%	86.7%	83.3%	78.6%	75.0%
Reinforcement Learning	44.4%	0.0%	11.1%	93.3%	77.8%	50.0%	53.7%
Autonomous Behavior	33.3%	12.5%	0.0%	90.0%	70.8%	60.7%	54.2%

Due to the limited sample size, a non-parametric Kruskal-Wallis test was conducted to determine whether family adoption scores differed across all sectors. The test results are presented in Table 10.

Table 10

Kruskal-Wallis Results for Sector-Level Variation

FAMILY	H-Statistic	Df	P-Value	Sig
Unsupervised Learning	11.14	5	0.049	Yes *
Autonomous Behavior	14.91	5	0.011	Yes *
Supervised Learning	8.76	5	0.119	No
Ensemble Learning	10.33	5	0.066	No
Deep Learning	6.23	5	0.284	No
NLP	6.20	5	0.288	No
Reinforcement Learning	10.36	5	0.066	No

Note: *: $p < 0.05$, two-tailed.

The test results identified statistically significant cross-sector variation for two of the seven families. The Autonomous Behavior family demonstrated the strongest variation across sectors ($H = 14.91$, $p = 0.011$). Its adoption was minimal in Healthcare and Commerce/e-Commerce, but substantially higher in Financial/Fintech (90%) and Engineering/Defense (70.8%), as shown in Table 9. The Unsupervised Learning family also showed significant variations across sectors ($H = 11.14$, $p = 0.049$). Adoption was absent in the Healthcare sector, compared with full adoption in the Financial/Fintech sector.

The Mann-Whitney U non-parametric test was applied to determine whether two sectors differ in their distributions.

Table 11

Significant Mann-Whitney U Pairwise Results for Sector Comparisons

FAMILY	Sector A	Sector B	Mean A	Mean B	U-Stat	p-Value
Autonomous Behavior	Commerce/E-Commerce	Financial/Fintech	0.000	0.900	0.00	0.022
Autonomous Behavior	Commerce/E-Commerce	Engineering/Defense	0.000	0.708	0.00	0.024
Autonomous Behavior	Commerce/E-Commerce	IT/Software	0.000	0.607	3.00	0.024
Unsupervised Learning	Healthcare	Financial/Fintech	0.000	1.000	0.00	0.028
Autonomous Behavior	Service	Financial/Fintech	0.333	0.900	3.50	0.034
Unsupervised Learning	Healthcare	IT/Software	0.000	0.786	2.00	0.034
Unsupervised Learning	Healthcare	Engineering/Defense	0.000	0.917	0.00	0.034

Note: ($p < 0.05$, two-tailed).

The most consistent sectoral pattern is that Autonomous Behavior adoption was significantly lower in Commerce/e-Commerce than in Financial/Fintech ($p = 0.022$), Engineering/Defense ($p = 0.024$), and IT/Software ($p = 0.024$), and lower in the Service sector than in Financial/Fintech ($p = 0.034$). Unsupervised Learning family adoption was significantly lower in Healthcare than in Financial/Fintech ($p = 0.028$), IT/Software ($p = 0.034$), and Engineering/Defense ($p = 0.034$).

Organizational stages: The normalized mean adoption rates of the AI algorithm families by organizational stage are presented in Table 12. A consistent upward pattern from pre-incubation to post-incubation was observed. The post-incubation stage achieved the highest adoption for all seven families, and the pre-incubation stage the lowest for five, within the start-up environment.

Table 12

Normalized AI Family Adoption by Organizational Stages

FAMILY	R&D N= 24	Pre Incubation N=4	Incubation N=5	Post- Incubation N=3	Sample Mean
Supervised Learning	67.4%	54.2%	86.7%	94.4%	70.8%
Unsupervised Learning	77.1%	50.0%	70.0%	100.0%	75.0%
Ensemble Learning	63.9%	66.7%	86.7%	88.9%	69.4%
Deep Learning	73.2%	53.6%	77.1%	95.2%	73.4%
NLP	72.2%	75.0%	80.0%	88.9%	75.0%
Reinforcement Learning	45.8%	58.3%	60.0%	100.0%	53.7%
Autonomous Behavior	49.0%	50.0%	55.0%	100.0%	54.2%

Post-incubation organizations achieved a 100% adoption score for Unsupervised Learning, Reinforcement Learning, and Autonomous Behavior. NLP showed the least stage variation (72.2%–88.9%), indicating broad deployment across all organizational stages. Reinforcement Learning showed the largest absolute range (45.8% at R&D versus 100% at Post-Incubation). R&D SMEs presented strong adoption in Unsupervised Learning, Deep Learning, and NLP. According to the results, Reinforcement Learning and Autonomous Behavior demonstrated slower diffusion.

A non-parametric Kruskal-Wallis test was applied to determine whether family adoption scores differed across all organizational stages. The test revealed statistically non-significant results for all AI families.

Discussion

This study aims to investigate AI adoption built on the proposed Expert-Driven Learning-Domain-Based AI taxonomy among R&D SMEs and start-ups operating in Türkiye. The analysis of findings sheds light on the patterns drawn from the seven AI families of the taxonomy and interpreted through the lens of the TOE framework, DOI, and DCT. Also, the study examines AI family adoption profiles, which are shaped by organizational sector and entrepreneurial stages.

Algorithm-level adoption frequency analysis shows that Decision Trees adoption comes first at 86.11%, followed closely by Neural Networks (83.33%), MLP (80.56%), and Linear Regression (80.56%). These results clearly indicate that widely adopted algorithms tend to be interpretable and structurally familiar. Decision Trees produce explicit splitting rules that practitioners can trace, verify, and explain to non-technical stakeholders. This aligns with the argument that R&D SMEs and start-ups need to demystify the AI black box (Dwivedi et al., 2021), and the most direct way to do so is to begin with models whose internal logic is visible. The relevance of Linear Regression similarly reflects a practical orientation. Organizations that need to explain predictions to clients, investors, or regulators adopt methods that produce accountable outputs like Linear Regression (Roustaei, 2024).

At the lower end of the adoption spectrum, Deep Q-Network, Policy Gradient, and SLAM are the least adopted algorithms, with each used by no more than half of the respondents. These algorithms share a common characteristic. They require an interactive environment for sequential decision-making, real-time sensor feedback, or both. The infrastructure needs alone distinguish them from the adoption-friendly profile of Decision Trees or Linear Regression. Rogers (2003) identifies perceived complexity as a principal barrier to innovation diffusion, and these algorithms represent precisely that barrier. Deploying them demands a level of operational infrastructure that most early-stage SMEs and start-ups have not yet constructed. Similarly, Hansen et al. (2024b) argue in the AI adoption context that complexity is driven less by intellectual difficulty than by the organization's readiness to absorb and implement technology.

The algorithms that fall between the upper and lower adoption tiers appear to be adopted by R&D SMEs and start-ups to broaden their implementation options rather than concentrating on a single area of expertise. This applied approach by the entrepreneurs and R&D SMEs is consistent with the AI-capability-building perspective

of DCT. In this perspective, early capability development involves selecting and implementing a broad range of tools before the organization has the expertise to strategically align them with its business needs (Mikalef et al., 2022).

The family-level analysis produces findings that are context-dependent. Although Unsupervised Learning and NLP reveal the same adoption rate (75.0%), the distribution of that adoption across organizations differs, demonstrating distinct usage patterns. Both showed median adoption of 100%, indicating that the majority of respondents who used these families adopted all constituent algorithms. The high standard deviations (38.73% and 35.97%, respectively) show that a substantial minority of organizations did not engage with these families at all, while those that did committed comprehensively. This pattern suggests that adoption of these families depends strongly on whether the family is relevant to a given operational context. NLP's position (75.0%) was consistent with the broad applicability of language models across all sectors except healthcare (Brown et al., 2020).

Ensemble Learning displays the most divergent distribution of all seven families. Among the 36 respondents, 66.67% adopted both constituent algorithms (AdaBoost and Stacking), whereas 27.78% adopted neither, leaving only two in an intermediate position. Practitioners appear to treat Ensemble Learning as an integrated approach rather than a flexible set of options. Organizations either embrace the principle of combining learners for variance reduction or do not adopt it at all. This all-or-nothing adoption logic is consistent with Mienye and Sun (2022), who note that ensemble methods are specifically adopted where single-model performance is insufficient, suggesting a deliberate response to a specific modeling problem rather than incremental experimentation.

Reinforcement Learning and Autonomous Behavior recorded the lowest mean adoption scores at 53.70% and 54.17%, respectively, and both exhibited the broadest standard deviations in the dataset. Reinforcement Learning, in particular, showed a dual-pattern distribution with 44.44% of respondents adopting all three RL algorithms, while 36.11% adopted none of them. This distribution signals a specialist/non-specialist divide that is not simply about resource availability. RL requires an interactive environment, a reward structure, and typically a simulation infrastructure before live deployment is possible. Organizations that have crossed those prerequisites tend to fully adopt RL. The observed pattern reflects the difference between RL and SL. Thus, RL demands more than technical effort; it also requires a different organizational readiness (Sutton & Barto, 1998; Brynjolfsson & McAfee, 2017).

The TOE framework predicts that environmental factors, including competitive context, sector norms, and data availability, shape the direction of technological investment (AlSheibani et al., 2018; Chen, H. et al., 2021). The sectoral analysis confirms this prediction in specific and interpretable ways. Financial/FinTech and Engineering/Defense demonstrated the broadest adoption portfolios, with normalized scores consistently above 70% across all seven families. Both sectors operate in data-rich, decision-intensive environments where the relative advantage of AI adoption is clear and measurable, which is a core predictor of DOI (AlSheibani et al., 2018). The performance gains from predictive analytics in financial and engineering applications justify the requirement for broader AI adoption.

The Healthcare sector presented a sharply contrasting profile, with zero adoption scores for Unsupervised Learning, Ensemble Learning, and Reinforcement Learning. The Deep Learning family showed moderate adoption at 35.7%, which reflects imaging and diagnostic applications where CNN-based architectures have established clinical credibility. Clinical decision-support tools require interpretable outputs and auditable reasoning chains; however, the black-box character of these methods conflicts with these requirements (Obermeyer & Emanuel, 2016). Thus, the absence of Unsupervised and Reinforcement approaches is consistent with the regulatory logic, as patterns in the analyzed data reflect institutional constraint rather than a lack of technical knowledge.

Commerce/e-Commerce showed zero adoption of the Autonomous Behavior family. SLAM, Kalman filtering, MPC, and RPA algorithms are sensor-embedded or process-automation technologies designed for physical-world operations. Digital commerce operations usually do not require complicated physical infrastructure, which these algorithms address. This precisely explains that the value of a technology is conditional and fits with the existing operational context, which aligns with the TOE framework's technological compatibility dimension (AlSheibani et al., 2018; Ayinaddis, 2025).

The Kruskal-Wallis tests confirmed statistically significant cross-sector variation for Autonomous Behavior ($H = 14.91$, $p = 0.011$) and Unsupervised Learning ($H = 11.14$, $p = 0.049$). The Mann-Whitney pairwise results further specified these differences. Autonomous Behavior adoption in Commerce/e-Commerce was significantly lower than in Financial/FinTech ($p = 0.022$), Engineering/Defense ($p = 0.024$), and IT/Software ($p = 0.024$). Since the same result was found in comparisons with three different sectors, the Commerce/e-Commerce finding reflects a systematic sectoral characteristic rather than a random result. Unsupervised Learning adoption in Healthcare was significantly lower than in Financial/FinTech ($p = 0.028$), IT/Software ($p = 0.034$), and Engineering/Defense ($p = 0.034$), reinforcing the regulatory-constraint interpretation.

Reinforcement Learning adoption was only 50.0%, making it the second lowest among sectors. The result may reflect the earlier observation that RL requires not just technical readiness but an interactive deployment environment. Therefore, software organizations that primarily build enterprise tools or analytics platforms may simply not have the application domains that RL addresses.

The organizational stage analysis reveals a directional pattern that is consistent with dynamic capability theory. Post-Incubation organizations achieved 100% normalized adoption for Unsupervised Learning, Reinforcement Learning, and Autonomous Behavior. However, these three families showed the lowest overall mean scores. This convergence at the post-incubation stage is theoretically coherent because organizations that progress through the full incubation trajectory have more time to sense opportunities in their data environments, to seize them through targeted capability building, and to transform their operations accordingly (Mikalef & Gupta, 2021). Also, this interpretation of incubation trajectory posits that each developmental transition unlocks access to new resources, which is in line with the stage-gate model, a popular system for driving new products to market (Cooper, 2008; Holub-Iwan et al., 2021; Leithold et al., 2015).

NLP showed the flattest variation across organizational stages, ranging from 72.2% at R&D to 88.9% at Post-Incubation. The possible explanation for this range is the relative accessibility of NLP algorithms. Models such as GPT and BERT can be accessed through APIs and do not require training from scratch (Y. Liu & Wang, 2026). This makes NLP more feasible for early-stage entrepreneurs with limited data and computational resources. This interpretation is consistent with the growing use of API-based AI among SMEs and start-ups (Y. Liu & Wang, 2026). However, this approach may also limit entrepreneurs' understanding of the underlying model and its functioning, which gives rise to the black-box conflict (Dwivedi et al., 2021).

The R&D stage itself showed considerable internal heterogeneity. This variance reflects the heterogeneous character of R&D organizations. Some are pre-commercial entities barely beyond ideation, while others are established entrepreneurs with dedicated AI development capacity. These results imply that R&D SMEs develop algorithms in simulation, unlike post-incubation entrepreneurs, who deploy algorithms in a physical product.

Implications

The findings make several contributions to the AI adoption literature. First, the algorithm-level focus of the analysis extends the TOE framework beyond its usual application to general AI adoption decisions. Previous studies have largely examined whether organizations adopt AI. In contrast, this study examines which algorithms they adopt and why the pattern varies. This provides a more precise understanding of how technological, organizational, and environmental factors shape adoption at the level of specific computational paradigms rather than AI as a single, undifferentiated technology.

Second, the study provides an empirical foundation for the black-box concern raised by Dwivedi et al. (2021). The adoption data show that R&D SMEs and start-ups do not adopt the full range of available algorithms uniformly. They cluster toward interpretable methods and commit differentially to dedicated AI families. This selective adoption pattern suggests that algorithm knowledge, the ability to distinguish what a method does and when it is appropriate, is already operating implicitly as a selection criterion. Making that criterion explicit, through a proposed Expert-Driven Learning-Domain-Based AI taxonomy, could help R&D SMEs and entrepreneurs make more deliberate decisions about where to build capability and where to apply off-the-shelf solutions.

Third, the dynamic capability perspective adds a developmental dimension to a static cross-sectional analysis. The stage-based pattern is broadly consistent with the sense-seize-transform logic of DCT (Mikalef & Gupta, 2021). Entrepreneurs at more mature stages tend to adopt a wider range of AI families. This suggests that AI adoption is not a one-time event, but a gradual process of capability development. Understanding which algorithm families mark each transition could inform how R&D SMEs and start-ups design their programs.

Several practical contributions are extracted from empirical findings. The findings suggest a pragmatic entry path that begins with interpretable supervised and unsupervised methods capable of generating immediate decision-making value for entrepreneurs in the early stages of AI adoption. Subsequently, adoption expands to more specialized families as operational infrastructure and data maturity increase. For governments, the results suggest that support and incentive programs should be tailored to sector-specific needs rather than based on a uniform AI literacy approach. Healthcare start-ups face institutional constraints that make certain AI algorithm families difficult to deploy, and support programs should address those constraints directly rather than treating them as capability deficits. For Financial/FinTech and Engineering/Defense entrepreneurs, the already-broad adoption profiles suggest readiness for deeper engagement with Reinforcement Learning and Autonomous Behavior families. Thus, knowledge and incentive supports should be directed towards necessary infrastructure investment for these types of entrepreneurs.

At the policy level, the study supports the argument that algorithm-level understanding should be a target of digital transformation for R&D SMEs and start-ups, not just AI tool adoption (Dwivedi et al., 2021). The results demonstrate that adopting AI and understanding AI are not the same thing. Organizations that embed AI models without knowing which algorithms drive them are unable to audit, debug, or adapt those models as circumstances change. Furthermore, a lack of AI algorithm literacy leads to uncontrolled data structures and outputs, which cause privacy and security risks. Thus, adoption without understanding AI algorithms' insights can easily manipulate businesses, personal behaviors, and actions. Consequently, off-the-shelf AI models supplied by the market may control both businesses' decision-making and personal consciousness.

The study contributes to a growing empirical literature on AI adoption in R&D SMEs and start-ups by shifting the analysis from the organizational level to the algorithm and algorithm-family level. Thereby, it introduces a seven-family, expert-driven learning-domain-based taxonomy grounded in the learning paradigm and validated by domain experts that contributes as a practical instrument for advancing the maturation of the AI taxonomy literature.

Limitations and Future Research

Several limitations can be drawn from this study. The most significant constraint is sample size. With 36 valid responses, the study can support descriptive and non-parametric analyses, but the power of those tests is limited. Relatedly, the sampling design is a non-probability convenience approach. In order to overcome the sample-collection issues, organizations should be encouraged by the regulatory body to reach the necessary sample size. A larger sample, ideally with more balanced representation across stages and sectors, is the most direct path to overcoming this constraint. The geographic scope introduces a second limitation. All 36 organizations are Turkish R&D SMEs and start-ups, and all are members of the Istanbul Chamber of Commerce. Türkiye has a specific regulatory, economic, and digital infrastructure context that shapes AI adoption in ways that may not generalize to other markets. The proposed taxonomy therefore awaits formal confirmatory factor-analytic validation on an adequately powered, ideally probability-based, multi-region sample. The cross-sectional design is a third limitation. Longitudinal data tracking the same organizations through their development stages would be needed to improve the study's explanations. Incorporating ordinal or continuous measures of adoption depth in future work would enrich the analysis considerably. Finally, self-reported survey data carry the usual risks of social desirability bias and recall inaccuracy. Validating adoption claims through technical audit or follow-up interviews would strengthen the measurement foundation for future studies.

References

- Abukmeil, M., Ferrari, S., Genovese, A., Piuri, V., & Scotti, F. (2022). A survey of unsupervised generative models for exploratory data analysis and representation learning. *ACM computing surveys*, 54(5). <https://doi.org/10.1145/3450963>
- Ahmed, S. F., Alam, M. S. Bin, Hassan, M., Rozbu, M. R., Ishtiak, T., Rafa, N., Mofijur, M., Shawkat Ali, A. B. M., & Gandomi, A. H. (2023). Deep learning modelling techniques: current progress, applications, advantages, and challenges. *Artificial intelligence review* (Vol. 56, Number 11). Springer Netherlands. <https://doi.org/10.1007/s10462-023-10466-8>
- Alekseev, A., & Strobel, C. (2026). A taxonomy of AI experiments. *Journal of behavioral and experimental economics*, 121, 102525. <https://doi.org/10.1016/j.socec.2026.102525>
- AlSheibani, S., Cheung, Y., & Messom, C. (2018). Artificial intelligence adoption: AI-readiness at firm-level. *Twenty-second pacific asia conference on information systems*. <https://sdaia.gov.sa/en/SDAIA/about/Files/AIAdoptionFramework.pdf>
- Aydiner, A. S., Ortaköy, S., & Özsürünç, Z. (2023). Employees' perception of value-added activity increase of Robotic Process Automation with time and cost efficiency: a case study. *International journal of information systems and project management*, 11(1), 30–49. <https://doi.org/10.12821/ijispm110102>
- Ayinaddis, S. G. (2025). Artificial intelligence adoption dynamics and knowledge in SMEs and large firms: A systematic review and bibliometric analysis. *Journal of innovation and knowledge*, 10(3), 100682. <https://doi.org/10.1016/j.jik.2025.100682>
- Bai, Y., Yan, B., Zhou, C., Su, T., & Jin, X. (2023). State of art on state estimation: Kalman filter driven by machine learning. *Annual reviews in control*, 56(October), 100909. <https://doi.org/10.1016/j.arcontrol.2023.100909>
- Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan, T., Child, R., Ramesh, A., Ziegler, D. M., Wu, J., Winter, C., ... Amodei, D. (2020). Language Models are Few-Shot Learners. *34th conference on neural information processing systems*. <https://commoncrawl.org/the-data/>
- Brynjolfsson, E., & McAfee, A. (2017). The business of artificial intelligence: What it can-and cannot-do for your organization *Harvard business review*, 7(1), 1-2.
- Chen, H., Li, L., & Chen, Y. (2021). Explore success factors that impact artificial intelligence adoption on telecom industry in China. *Journal of management analytics*, 8(1), 36–68. <https://doi.org/10.1080/23270012.2020.1852895>
- Chen, J., Zhou, W., & Frankwick, G. L. (2025). Firm AI Adoption Intensity and Marketing Performance. *Journal of computer information systems*, 65(2), 172–189. <https://doi.org/10.1080/08874417.2023.2277751>
- Cho, E. (2016). Making reliability reliable: A systematic approach to reliability coefficients. *Organizational research methods*, 19(4), 651–682.
- Chowdhury, S., Dey, P., Joel-Edgar, S., Bhattacharya, S., Rodriguez-Espindola, O., Abadie, A., & Truong, L. (2023). Unlocking the value of artificial intelligence in human resource management through AI capability framework. *Human resource management review*, 33(1), 100899. <https://doi.org/10.1016/j.hrmr.2022.100899>
- Cooper, R. G. (2008). Perspective: The stage-gates® idea-to-launch process - Update, what's new, and NexGen systems. *Journal of product innovation management*, 25(3), 213–232. <https://doi.org/10.1111/j.1540-5885.2008.00296.x>
- Cortina, J. M. (1993). What is coefficient alpha? An examination of theory and applications. *Journal of applied psychology*, 78(1), 98–104.
- Crocker, L., & Algina, J. (1986). *Introduction to classical and modern test theory*. Orlando, FL: Wadsworth Publishing.

- Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. *NAACL HLT 2019 - 2019 Conference of the north american chapter of the association for computational linguistics: human language technologies - proceedings of the conference, 1*, 4171–4186.
- DeVellis, R. F., & Thorpe, C. T. (2022). *Scale development: Theory and applications, fifth edition*. California: SAGE Publications.
- de Winter, J. C. F., Dodou, D., & Wieringa, P. A. (2009). Exploratory factor analysis with small sample sizes. *Multivariate behavioral research*, 44(2), 147–181.
- Dillman, D. A. (2007). *Mail and Internet surveys: The tailored design method--2007 update with new Internet, visual, and mixed-mode guide*. New Jersey, Hoboken: John Wiley & Sons Inc.
- Ding, Y., Wang, L., Li, Y., & Li, D. (2018). Model predictive control and its application in agriculture: A review. *Computers and electronics in agriculture*, 151(December 2017), 104–117. <https://doi.org/10.1016/j.compag.2018.06.004>
- Du-Harpur, X., Watt, F. M., Luscombe, N. M., & Lynch, M. D. (2020). What is AI? Applications of artificial intelligence to dermatology. *British journal of dermatology*, 183(3), 423–430. <https://doi.org/10.1111/bjd.18880>
- Dutta, A. (2025). *Taxonomy of artificial intelligence*. Ericson Canada Inc.
- Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., ... Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International journal of information management*, 57(August 2019), 101994. <https://doi.org/10.1016/j.ijinfomgt.2019.08.002>
- Eckhardt, C. M., Madjarova, S. J., Williams, R. J., Ollivier, M., Karlsson, J., Pareek, A., & Nwachukwu, B. U. (2023). Unsupervised machine learning methods and emerging applications in healthcare. *Knee surgery, sports traumatology, arthroscopy*, 31(2), 376–381. <https://doi.org/10.1007/s00167-022-07233-7>
- Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). Comparison of convenience sampling and purposive sampling. *American journal of theoretical and applied statistics*, 5(1), 1–4.
- Fabregat-Hernández, A., Palanca, J., & Botti, V. (2023). Exploring explainable AI: category theory insights into machine learning algorithms. *Machine learning: science and technology*, 4(4). <https://doi.org/10.1088/2632-2153/ad1534>
- Fiorini, S. R., Carbonera, J. L., Gonçalves, P., Jorge, V. A. M., Rey, V. F., Haidegger, T., Abel, M., Redfield, S. A., Balakirsky, S., Ragavan, V., Li, H., Schlenoff, C., & Prestes, E. (2015). Extensions to the core ontology for robotics and automation. *Robotics and computer-integrated manufacturing*, 33, 3–11. <https://doi.org/10.1016/j.rcim.2014.08.004>
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research* (Vol. 18, Number 1, pp. 39–50).
- Gama, F., & Magistretti, S. (2025). Artificial intelligence in innovation management: A review of innovation capabilities and a taxonomy of AI applications. *Journal of product innovation management*, 42(1), 76–111. <https://doi.org/10.1111/jpim.12698>
- Gama, J., & Brazdil, P. (1995). Characterization of classification algorithms. *Portuguese conference on artificial intelligence*, 189–200.
- Gheisari, M., Ebrahimzadeh, F., Rahimi, M., Moazzamigodarzi, M., Liu, Y., Dutta Pramanik, P. K., Heravi, M. A., Mehbodniya, A., Ghaderzadeh, M., Feylizadeh, M. R., & Kosari, S. (2023). Deep learning: Applications, architectures, models, tools, and frameworks: A comprehensive survey. *CAAI transactions on intelligence technology*, 8(3), 581–606. <https://doi.org/10.1049/cit2.12180>

- Gill, S. S., Golec, M., Hu, J., Xu, M., Du, J., Wu, H., Walia, G. K., Murugesan, S. S., Ali, B., Kumar, M., Ye, K., Verma, P., Kumar, S., Cuadrado, F., & Uhlig, S. (2025). Edge AI: A taxonomy, systematic review and future directions. *Cluster computing*, 28(1). <https://doi.org/10.1007/s10586-024-04686-y>
- Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage.
- Hair, J. F., Money, A. H., Samouel, P., & Page, M. (2007). *Research methods for business*. New York, NY: Wiley.
- Hansen, H. F., Lillesund, E., Mikalef, P., & Altwaijry, N. (2024). Understanding artificial intelligence diffusion through an ai capability maturity model. *Information systems frontiers*, 26(6), 2147–2163. <https://doi.org/10.1007/s10796-024-10528-4>
- Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The elements of statistical learning: data mining, inference, and prediction, second edition*. Springer.
- Hayes, A. F., & Coutts, J. J. (2020). Use omega rather than Cronbach's alpha for estimating reliability. *Communication methods and measures*, 14(1), 1–24.
- Holub-Iwan, J., Kupczyk, T., Debita, G., & Rupa, P. (2021). Leadership and effectiveness of incubation of start-ups: research scheme for next generation stage gate. *European research studies journal*, XXIV(4), 797–818.
- Hossain, M. A., Agnihotri, R., Rushan, M. R. I., Rahman, M. S., & Sumi, S. F. (2022). Marketing analytics capability, artificial intelligence adoption, and firms' competitive advantage: Evidence from the manufacturing industry. *Industrial marketing management*, 106, 240–255. <https://doi.org/10.1016/j.indmarman.2022.08.017>
- Jiang, T., Gradus, J. L., & Rosellini, A. J. (2020). Supervised machine learning: a brief primer. *Behavior therapy*, 51(5), 675–687. <https://doi.org/10.1016/j.beth.2020.05.002>
- Leithold, N., Haase, H., & Lautenschläger, A. (2015). Stage-gate® for SMEs: a qualitative study in Germany. *European journal of innovation management*, 18(2), 130–149. <https://doi.org/10.1108/EJIM-07-2014-0070>
- Liu, Y. T., Yang, J. M., Chen, L., Guo, T., & Jiang, Y. (2020). Overview of reinforcement learning based on value and policy. *Proceedings of the 32nd Chinese control and decision conference, CCDC 2020*, 598–603. <https://doi.org/10.1109/CCDC49329.2020.9164615>
- Liu, Y., & Wang, H. (2026). Who on earth is using generative AI? *World development*, 199(November 2025), 107260. <https://doi.org/10.1016/j.worlddev.2025.107260>
- Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. *Conference on human factors in computing systems - Proceedings*, 1–16. <https://doi.org/10.1145/3313831.3376727>
- Lu, Y. (2019). Artificial intelligence: a survey on evolution, models, applications and future trends. *Journal of management analytics*, 6(1), 1–29. <https://doi.org/10.1080/23270012.2019.1570365>
- MacCallum, R. C., Widaman, K. F., Zhang, S., & Hong, S. (1999). Sample size in factor analysis. *Psychological methods*, 4(1), 84–99.
- McDonald, R. P. (2011). *Test theory: A unified treatment*. New York, NY: Routledge Taylor & Francis Group.
- Mienye, I. D., & Sun, Y. (2022). A survey of ensemble learning: concepts, algorithms, applications, and prospects. *IEEE access*, 10(August), 99129–99149. <https://doi.org/10.1109/ACCESS.2022.3207287>
- Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information and management*, 58(3). <https://doi.org/10.1016/j.im.2021.103434>
- Mikalef, P., Lemmer, K., Schaefer, C., Ylinen, M., Fjortoft, S. O., Torvatn, H. Y., Gupta, M., & Niehaves, B. (2022). Enabling AI capabilities in government agencies: A study of determinants for European municipalities. *Government information quarterly*, 39(4). <https://doi.org/10.1016/j.giq.2021.101596>

- Mohri, M., Rostamizadeh, A., & Talwalkar, A. (2018). *Foundations of machine learning (2nd ed.)*. The MIT Press. www.dbooks.org
- Mollick, E. (2024). *Co-intelligence: living and working with AI*. New York: Penguin Random House LLC.
- Nagahisarchoghaei, M., Nur, N., Cummins, L., Nur, N., Karimi, M. M., Nandanwar, S., Bhattacharyya, S., & Rahimi, S. (2023). An empirical survey on explainable AI technologies: recent trends, use-cases, and categories from technical and application perspectives. *Electronics (Switzerland)*, 12(5). <https://doi.org/10.3390/electronics12051092>
- Nunnally, J. C. (1978). *Psychometric theory (2nd ed.)*. McGraw-Hill Book Company.
- Obermeyer, Z., & Emanuel, E. J. (2016). Predicting the future — big data, machine learning, and clinical medicine. *New england journal of medicine*, 375(13), 1216–1219. <https://doi.org/10.1056/nejmp1606181>
- OECD. (2025). AI adoption by small and medium-sized enterprises: OECD discussion paper for the G7. *AI adoption by small and medium-sized enterprises*. https://www.oecd.org/en/publications/ai-adoption-by-small-and-medium-sized-enterprises_426399c1-en.html
- Pramod, D. (2022). Robotic process automation for industry: adoption status, benefits, challenges and research agenda. *Benchmarking*, 29(5), 1562–1586. <https://doi.org/10.1108/BIJ-01-2021-0033>
- Prestes, E., Carbonera, J. L., Rama Fiorini, S., Vitor, V. A., Abel, M., Madhavan, R., Locoro, A., Goncalves, P., E. Barreto, M., Habib, M., Chibani, A., Gérard, S., Amirat, Y., & Schlenoff, C. (2013). Towards a core ontology for robotics and automation. *Robotics and autonomous systems*, 61(11), 1193–1204. <https://doi.org/10.1016/j.robot.2013.04.005>
- Radhakrishnan, J., & Chattopadhyay, M. (2020). Determinants and barriers of artificial intelligence adoption – A literature review. *IFIP advances in information and communication technology*, 617, 89–99. https://doi.org/10.1007/978-3-030-64849-7_9
- Raiaan, M. A. K., Mukta, M. S. H., Fatema, K., Fahad, N. M., Sakib, S., Mim, M. M. J., Ahmad, J., Ali, M. E., & Azam, S. (2024). A review on large language models: architectures, applications, taxonomies, open issues and challenges. *IEEE access*, 12(January), 26839–26874. <https://doi.org/10.1109/ACCESS.2024.3365742>
- Rana, A., Rawat, A. S., Bijalwan, A., & Bahuguna, H. (2018). Application of multi layer (perceptron) artificial neural network in the diagnosis system: a systematic review. *Proceedings of the 2018 3rd IEEE international conference on research in intelligent and computing in engineering, RICE 2018*, 1–6. <https://doi.org/10.1109/RICE.2018.8509069>
- Revelle, W., & Condon, D. M. (2019). Reliability from α to ω : A tutorial. *Psychological assessment*, 31(12), 1395–1411. <https://doi.org/10.1037/pas0000754>
- Rogers, E. M. (2003). *Diffusion of innovations, Fifth Edition*. Free Press.
- Roustaei, N. (2024). Application and interpretation of linear regression analysis. *Medical hypothesis, discovery, and innovation in ophthalmology*, 13(3), 151–159. <https://doi.org/10.51329/mehdiophthal1506>
- Schapire, R. E. (2013). *Explaining AdaBoost* (pp. 37–52). Springer Berlin Heidelberg.
- Shakya, A. K., Pillai, G., & Chakrabarty, S. (2023). Reinforcement learning algorithms: A brief survey. *Expert systems with applications*, 231(April), 120495. <https://doi.org/10.1016/j.eswa.2023.120495>
- Shao, M., Basit, A., Karri, R., & Shafique, M. (2024). Survey of different large language model architectures: trends, benchmarks, and challenges. *IEEE access*, 12, 188664–188706. <https://doi.org/10.1109/ACCESS.2024.3482107>
- Sutton, R. S., & Barto, A. G. (1998). *Reinforcement learning: An introduction*. The MIT Press.
- Talbi, E.-G. (2020). *Optimization of deep neural networks: a survey and unified taxonomy*. <https://inria.hal.science/hal-02570804v2>
- Tavakol, M., & Dennick, R. (2011). Making sense of cronbach's alpha. *International journal of medical education* (Vol. 2, pp. 53–55). <https://doi.org/10.5116/ijme.4dfb.8dfd>

- Uren, V., & Edwards, J. S. (2023). Technology readiness and the organizational journey towards AI adoption: An empirical study. *International journal of information management*, 68(September 2022), 102588. <https://doi.org/10.1016/j.ijinfomgt.2022.102588>
- Valkenborg, D., Rousseau, A. J., Geubbelmans, M., & Burzykowski, T. (2023). Support vector machines. *American journal of orthodontics and dentofacial orthopedics* (Vol. 164, Number 5, pp. 754–757). Elsevier Inc. <https://doi.org/10.1016/j.ajodo.2023.08.003>
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, 27(3), 425–478.
- Wadud, M. A. H., Mridha, M. F., & Rahman, M. M. (2022). Word embedding methods for word representation in deep learning for natural language processing. *Iraqi journal of science*, 63(3), 1349–1361. <https://doi.org/10.24996/ijis.2022.63.3.37>
- Wu, C., Zhang, R., Kotagiri, R., & Bouvry, P. (2023). Strategic decisions: survey, taxonomy, and future directions from an artificial intelligence perspective. *ACM computing surveys* (Vol. 55, Number 12). Association for Computing Machinery. <https://doi.org/10.1145/3571807>
- Zebec, A., & Indihar Štemberger, M. (2020). Conceptualizing a capability-based view of artificial intelligence adoption in a BPM context. *Lecture notes in business information processing*, 397, 194–205. https://doi.org/10.1007/978-3-030-66498-5_15

Genişletilmiş Özet

Amaç

Bu çalışma, Türkiye'deki araştırma-geliştirme (AR-GE) odaklı küçük ve orta ölçekli işletmeler (KOBİ'ler) ile girişim şirketlerinin yapay zekâ (YZ) benimseme örüntülerini algoritma düzeyinde incelemeyi amaçlamaktadır. Mevcut literatürde YZ benimseme araştırmalarının büyük çoğunluğu, YZ'yi tek ve bütünleşik bir teknoloji olarak ele almakta; hangi algoritmaların benimsendiğine ve bu seçimlerin nedenlerine ilişkin bilgi son derece sınırlı kalmaktadır (AlSheibani et al., 2018; Chen, H. et al., 2021). Ayrıca mevcut YZ taksonomi çalışmalarının büyük bölümü kavramsal ya da paradigma düzeyinde kalmakta, algoritmaların uygulama bağlamında seçilmesi ve karşılaştırılması için pratik bir rehberlik sunmamaktadır (Dutta, 2025).

Bu boşluğu gidermek amacıyla çalışma üç temel araştırma sorusunu yanıtlamayı hedeflemektedir:

- 1- AR-GE KOBİ'leri ve girişim şirketleri tarafından hangi YZ algoritmaları en sık benimsenmektedir?
- 2- Farklı organizasyonel sektörlerde hangi YZ algoritma aileleri daha yaygın olarak benimsenmektedir?
- 3- Farklı organizasyonel aşamalarda hangi YZ algoritma aileleri daha sık benimsenmektedir?

Çalışmanın nihai hedefi, yedi algoritma ailesini (Denetimli Öğrenme, Denetimsiz Öğrenme, Takviyeli Öğrenme, Derin Öğrenme, Doğal Dil İşleme, Topluluk Öğrenmesi ve Otonom Davranış) kapsayan uzman odaklı, öğrenme alanı tabanlı bir YZ taksonomisi aracılığıyla benimseme frekanslarını ortaya koymaktır. Çalışma ayrıca Teknoloji-Organizasyon-Çevre (TOE) çerçevesini, Yenilik Yayılımı (DOI) ve Dinamik Yetenek Teorisi (DCT) ile birlikte algoritma düzeyine taşıyarak ilgili literatüre kuramsal bir katkı sunmayı hedeflemektedir. Bu araştırma AR-GE KOBİ'leri ve girişim şirketlerinin karşılaştığı "kara kutu" problemini, yani API tabanlı ya da hazır YZ araçlarını arka plandaki algoritmayı bilmeden kullanmalarından kaynaklanan şeffaflık, hesap verebilirlik ve stratejik uyum eksikliklerini (Dwivedi et al., 2021; Y. Liu & Wang, 2026) ortaya koyan ve çözüm üreten bir çalışmadır.

Yöntem

Çalışma, İstanbul Ticaret Odası üyesi 36 Türk AR-GE KOBİ'si ve girişim şirketinden anket yoluyla nicel veri toplayan uygulamalı ve betimsel bir araştırma tasarımına sahiptir. Anket; YZ uygulayıcıları, geliştiriciler ve akademisyenlerle derinlemesine görüşmeler aracılığıyla geliştirilen, 28 algoritmayı kapsayan ve uzman odaklı öğrenme alanı tabanlı bir YZ taksonomisi üzerine inşa edilmiştir. Beşli Likert ölçeğiyle hazırlanan anket önce Türkçeye çevrilmiş, ardından geri çevirisi yapılarak dil tutarlılığı doğrulanmıştır. İçerik geçerliliği, alan uzmanlarından alınan geri bildirimler doğrultusunda sistematik biçimde sağlanmıştır (Hair et al., 2007). İstanbul Medeniyet Üniversitesi Sosyal Bilimler Etik Kurulu'ndan etik onay alınmıştır.

Ana kütleyi Türkiye'deki AR-GE KOBİ'leri ve girişim şirketlerinde aktif görev yapan YZ geliştiricileri, yöneticiler ve uygulayıcılar oluşturmaktadır. Örneklem sürecinde İstanbul Ticaret Odası üyesi 38 kuruluşa ulaşılmış; veri ön işleme aşamasında iki kuruluş eksik bilgi nedeniyle elenmiş ve geçerli yanıt sayısı 36 olarak belirlenmiştir. Veri toplama, SurveyMonkey platformu üzerinden e-posta ve LinkedIn kanallarıyla gerçekleştirilmiştir. Katılımcılar; AR-GE, ön kuluçka, kuluçka ve kuluçka sonrası aşamalar olmak üzere Mungila Hillemane et al. (2019) çalışmasıyla uyumlu biçimde sınıflandırılmıştır.

Güvenilirlik için Cronbach alfa ve McDonald omega değerleri hesaplanmış; geçerlilik için bileşik güvenilirlik (CR) ve açıklanan ortalama varyans (AVE) ölçütleri incelenmiştir. Küçük örneklem büyüklüğü (N=36) nedeniyle betimsel istatistikler ve parametrik olmayan analizler tercih edilmiş; sektörler arası farklılıklar için Kruskal-Wallis ve Mann-Whitney U testleri uygulanmıştır. Analizler Python programlama diliyle Pandas ve NumPy paketleri kullanılarak gerçekleştirilmiştir.

Bulgular

Algoritma düzeyinde benimseme frekans analizi, en çok benimsenen algoritmanın Karar Ağaçları (f=31; %86,11) olduğunu ortaya koymuştur. Bunu Sinir Ağları (%83,33), Çok Katmanlı Algılayıcı (MLP) ve Doğrusal Regresyon (%80,56) izlemektedir. Bu algoritmaların yüksek benimseme oranları, yorumlanabilirlik ve yapısal tanışıklıkla

doğrudan ilişkilendirilmektedir (Breiman, 2001; Hastie et al., 2009). En az benimsenen algoritmalar ise Derin Q-Ağı, Politika Gradyanı (%50,00) ve SLAM (%47,22) olmuştur.

Aile düzeyinde Denetimsiz Öğrenme ve Doğal Dil İşleme en yüksek ortalama benimseme oranlarına ulaşmıştır (her ikisi de %75,00). Takviyeli Öğrenme (%53,70) ve Otonom Davranış (%54,17) ise en düşük benimseme oranlarını vermiştir. Topluluk Öğrenmesi, "ya hep ya hiç" şeklinde bir benimseme örüntüsü ortaya koymuştur. Katılımcıların %66,67'si her iki algoritmayı da benimserken, %27,78'i hiçbirini benimsememiştir.

Sektörel analizde Finans/FinTech ve Mühendislik/Savunma tüm yedi ailede %70'in üzerinde benimseme oranıyla en geniş portfolyolara sahip olmuştur. Sağlık sektörü ise Denetimsiz Öğrenme, Topluluk Öğrenmesi ve Takviyeli Öğrenme ailelerinde sıfır benimseme oranı kaydetmiştir. Ticaret/e-Ticaret sektöründe Otonom Davranış ailesi hiç benimsenmemiştir. Kruskal-Wallis testi, Otonom Davranış ($H=14,91$; $p=0,011$) ve Denetimsiz Öğrenme ($H=11,14$; $p=0,049$) ailelerinde sektörler arası istatistiksel açıdan anlamlı farklılıklar tespit etmiştir. Mann-Whitney U testi bu farklılıkların belirli sektör çiftlerine özgü olduğunu doğrulamıştır.

Organizasyonların gelişim aşaması analizinde kuluçka sonrası aşamadaki kuruluşlar, tüm yedi ailede en yüksek benimseme oranlarına ulaşmıştır. Takviyeli Öğrenme, en geniş aşama aralığını (AR-GE'de %45,8 ile kuluçka sonrasında %100) ortaya koymuştur.

Sınırlılıklar

Çalışmanın en önemli sınırlılığı örneklem büyüklüğüdür. 36 geçerli yanıt, betimsel ve parametrik olmayan analizleri desteklemekle birlikte bu testlerin istatistiksel gücünü kısıtlamaktadır. Bazı sektörlerdeki alt örneklem büyüklükleri, sektör karşılaştırmalarının güvenilirliğini sınırlandırmaktadır.

İkinci önemli sınırlılık coğrafi kapsam ile ilgilidir. Çalışmanın tüm katılımcıları İstanbul Ticaret Odası üyesi Türk AR-GE KOBİ'leri ve girişim şirketlerinden oluşmaktadır. Türkiye'nin kendine özgü düzenleyici, ekonomik ve dijital altyapı bağlamı, bulguların başka ülkelere genellenebilirliğini kısıtlamaktadır.

Kesitsel araştırma tasarımı da bir sınırlılık olarak değerlendirilmektedir. Aynı kuruluşları farklı gelişim aşamalarında izleyen boylamsal veriler, aşama temelli yorumlamaları çok daha güçlü kılacaktır. Benimsemenin derinliğini ölçen sürekli ya da ordinal ölçütlerin gelecek çalışmalara eklenmesi analizi zenginleştirecektir.

Son olarak, öz bildirim dayalı anket verisi sosyal beğenirlik yanlılığı ve hatırlama hataları gibi bilinen riskleri beraberinde getirmektedir. Teknik denetim ya da takip görüşmeleriyle benimseme iddialarının doğrulanması, gelecekteki çalışmaların ölçüm temelini sağlamlaştıracaktır.

Öneriler

Çalışma, kuramsal, pratik ve politika açısından çok boyutlu katkılar sunmaktadır. Kuramsal düzeyde TOE çerçevesi, DOI teorisi ve DCT bütünleşik bir YZ teknolojisi yerine belirli algoritmalar ve algoritma aileleri düzeyine taşınmıştır. Bu yaklaşım, teknolojik, organizasyonel ve çevresel faktörlerin hesaplama paradigmaları üzerindeki etkisini daha ayrıntılı biçimde açıklamaktadır. Ayrıca çalışma, Dwivedi et al. (2021) tarafından dile getirilen kara kutu sorununa ampirik bir zemin kazandırmaktadır. Benimseme verileri, algoritma bilgisinin örtük bir seçim kriteri olarak işlev gördüğünü ortaya koymaktadır.

Pratik açıdan, bulgular girişimciler için yorumlanabilir, denetimli ve denetimsiz yöntemlerle başlayan pragmatik bir giriş yolu önermektedir. Operasyonel altyapı ve veri olgunluğu arttıkça, benimseme daha özelleşmiş ailelere doğru genişletilmelidir. Politika yapıcılar ve kamusal destek kurumları için sonuçlar, sektöre özel gereksinimler doğrultusunda farklılaştırılmış destek ve teşvik programlarının tasarlanması gerektiğine işaret etmektedir. Sağlık girişimleri kurumsal kısıtlamalarla karşı karşıya olduğundan, ilgili programlar bu kısıtlamaları doğrudan hedef çözümlerle ele almalıdır. Finans/FinTech ve Mühendislik/Savunma girişimcileri için Takviyeli Öğrenme ve Otonom Davranış altyapısına yönelik bilgi ve teşvik destekleri yönlendirilmelidir.

Bu çalışma, algoritma düzeyinde anlayışın AR-GE KOBİ'lerinin ve girişim şirketlerinin dijital dönüşümü için bir hedef olması gerektiğini savunmaktadır (Dwivedi et al., 2021). YZ'yi benimsemek ile YZ'yi anlamak aynı şey

değildir; altta yatan algoritmayı bilmeden benimseme, denetimi, hata ayıklamayı ve uyarlamayı güçleştirmekte ve gizlilik/güvenlik risklerini artırmaktadır.

Özgün Değer

Bu çalışmanın özgün değeri, YZ benimseme araştırmalarını organizasyonel düzeyden algoritma ve algoritma ailesi düzeyine taşıması ve bu amaçla orijinal bir model geliştirmesinde yatmaktadır. Çalışma, yedi aile ve 28 algoritmadan oluşan uzman odaklı öğrenme alanı tabanlı YZ taksonomisini sunmaktadır. Bu taksonomi, öğrenme paradigması etrafında yapılandırılmış, YZ konusunda çalışan akademisyenler, sektör uzmanları tarafından doğrulanmış ve Gama ve Brazdil (1995) tarafından önerilen bölümlleme algoritması çerçevesiyle uyumlu hale getirilmiştir.

Mevcut YZ taksonomi çalışmalarının büyük çoğunluğu kavramsal ya da paradigma düzeyinde kalmaktadır. Bu çalışma, taksonomisini doğrudan algoritma düzeyinde konumlandırarak AR-GE KOBİ'leri ve girişim şirketleri için pratik seçim ve uygulama rehberliği sunmaktadır (Dutta, 2025). Önerilen taksonomi, AlSheibani et al. (2018) ve Chen, H. et al. (2021) tarafından vurgulanan algoritma düzeyindeki benimseme açığını kapatmaktadır.

Çalışma aynı zamanda TOE çerçevesini, DOI teorisini ve DCT ile birlikte genel YZ benimseme analizinin ötesine taşıyarak sektörel ve gelişim aşaması boyutlarını birleştirmektedir. Çalışmanın pratik katkısı olarak geliştirilen taksonomi, girişimciler, hızlandırıcılar ve politika yapıcılar için algoritma düzeyinde kapasite geliştirmeyi yönlendirmeye yönelik yapılandırılmış bir araç işlevi görmektedir. Son olarak, çalışma Türk AR-GE KOBİ'leri ve girişim şirketleri bağlamındaki ampirik bulgularıyla bu alanda uluslararası karşılaştırmalı araştırmalar için bir referans noktası oluşturmaktadır.