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Artificial Intelligence Readiness and Adoption in Firms

Lingling MA
Sofia University St. Kliment Ohridski
ma.lingling.st@gmail.com

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Abstract
The purpose of this study is to exploring the factors related to readiness for Artificial Intelligence (AI) adoption and to examine the current state of AI adoption practices among firms in Bulgaria. This study examines the factors related to AI technology innovation based on the technology-organization-environment (TOE) model. Four critical factors related to AI adoption are identified. The result is empirically tested with data collected by online survey filled by firms in Bulgaria. Factor analysis and cluster analysis is applied to analyze the data. The study found data, AI awareness and attitude, external funding are significantly related to readiness to AI adoption. Also a typology of four player types within the Bulgarian AI landscape is formed. Leaders are more innovative; catch-uppers have the highest AI planning intensity; wannabe firms are not yet ready in terms of budget and planning strategy; and laggards are similar to "wannabes". Additionally, practical implications and recommendations for management leaders are provided to better shape the awareness and attitude on AI itself, and to offer tailored support services to different types of companies.

Keywords: AI Readiness and Adoption, Bulgarian firms, TOE framework, Clusters.

JEL classification: O33, M15, L20.

Introduction

In the rapid evolving digital landscape, artificial intelligence (AI) has emerged as a transformative force. Broadly AI defined as the capability of machines to imitate intelligent human behavior, such as learning, reasoning, and decision-making. The coverage of big data, advanced algorithms, and increased computer power has propelled AI from research labs into the mainstream of business strategy. AI offers firms unprecedented opportunities to enhance productivity, optimize decision-making, and foster innovation. AI reshapes industries and redefines competitive dynamics across the globe.

Within this global context, Bulgaria, as a member of the European Union, is witnessing a gradual but promising uptake of AI. Desisleva et al. (2023) reported that 3.6% of firms using AI technologies. This adoption rate is notably higher among larger companies (13.8%) compared to medium (5.5%) and small enterprises (3.0%). Funding from EU projects significantly increased the likelihood of companies engaging in innovation activities. For instant, technological innovation in agricultural firms in Bulgaria (Lingling Ma, 2024), this study discovered the crucial role of EU funding in enhancing the growth of agro-sector. Likewise, Velichkov et al. (2024) concluded that 31% of companies got involved in more than one EU project, and 64% of companies won one EU project. They do really have a better performance in process innovation, product innovation, and market innovation, compared with companies which do not participate in EU projects. Additionally, Velichkov et al. (2024) concluded that 18% of companies that implemented EU projects also execute AI solutions.

For firms to successfully navigate the AI landscape, they must traverse a path from initial preparedness to full-scale implementation. This study focuses on two critical concepts along the journey. AI readiness is defined as preparedness at the organizational level for the intention to adopt AI. It encompasses the assessment of necessary technological infrastructure, the availability and quality of data, the presence of skilled talent, and the commitment of leadership to foster a culture of innovation. Readiness is a pre-adoption phase. AI adoption in the context of this paper is defined as the actual usage of AI applications in the firms. This move beyond intention to tangible action, such as implementing chatbots for customer service, using machine learning models for sales forecasting, or deploying robotics for process automation.

Most dominant theories in studying accepting new technologies were Technology-Organization-Environment (TOE) framework, DOI theory, UTAUT, TAM, and others. A body of research has examined the challenges that need to be conquered to achieve widespread adoption of AI. Looking more into the AI challenges, there is a wealth of literature studying the factors driving or hindering the implementation of AI cases within organizations, regarding to technological, organizational, and environmental context.

Scholars also have derived several theoretical models and frameworks that explain or predict the various factors associated with users' acceptance of technology and applications of AI. Some researchers asserted that some of the components in some of the above theoretical models are not relevant or applicable to AI context. Therefore, they further proposed several kinds of theory to study AI adoption, because of the unique of AI. Similarly, researchers have extensively explored the approaches of deploying AI, namely AI readiness framework, or AI maturity/adoption model. The project of prompting AI implementation have been carried out by various countries, such as Asian countries, west European countries, south Africa, etc. However, there is very limited volume of research about the AI landscape in Bulgaria.

This research aims to exploring the factors related to readiness for Artificial Intelligence (AI) adoption and to examine the current state of AI adoption practices among firms in Bulgaria. By examining the extent to which businesses in Bulgaria are prepared to integrate AI technologies into their operations, this study seeks to provide insights into factors that related to AI adoption and the potential impact on the country's economic landscape. To achieve this goal, the study makes a review of literature on factors influencing AI readiness and/or AI adoption, followed by a quantitative approach using a survey to collect data from 81 companies and measure constructs/variables, and to identify the factors related to significant differences between groups of companies in respect to technological, organizational, and environmental factors, related to the AI readiness and adoption. Factor analysis and two cluster analyses are used to group samples in terms of their readiness on AI awareness, Attitudes, and Obstacles.

Furthermore, the finding of this study contribute to empirical research on factors in the technology-organization-environment context that influence AI adoption. Given the importance of integrating AI in business operation, the findings of this study are expected to assist change management leader and AI service provider in targeting appropriate factors at readiness level and executing wise strategy to AI adoption.

1. Literature review

1.1. Artificial Intelligence (AI) and its adoption: a conceptual overview

The official concept of Artificial Intelligence (AI) was first coined by John McCarthy at the Dartmouth conference in 1956. AI is generally used to describe machines or computers that mimic "cognitive" functions that humans associate with the human mind, such as "learning", and "problem solving" (Russell & Norvig, 2020). Beyond this, AI is increasingly emphasized as a data-driven technology. For instance, Kaplan & Haenlein (2019) defines AI as the system's ability to interpret external data to learn from such data and to use those learning and to achieve specific goals and tasks through flexible adaptation.

In this study, AI readiness is defined as preparedness at the organizational level for the intention to adopt AI. It encompasses factors such as the assessment of necessary technological infrastructure, the availability and quality of data, the presence of skilled talent, and the commitment of leadership to foster a culture of innovation. Thus, Readiness is a pre-adoption phase. This requires firms to obtain a clear checklist of organizational performance. On the other hand, AI adoption is defined here as the actual usage of AI applications within firms. This represents a shift beyond intention to tangible action.

In business context, Singla et al. (2025) defines AI adoption as the application of AI technologies within business strategies and operations to achieve optimization and strategic goals. They place significant emphasis on the practical implementation of AI across various business functions. As Statista (2025) reported, the AI market is structured into six segments based on the technology. Firstly, the Computer Vision segment covers applications that enable computers to interpret and understand digital images and video data. Secondly, the Machine Learning segment covers the use of algorithms to enable computer systems to learn from data. Thirdly, the Natural Language Processing segment covers applications that enable computers to understand, interpret, and generate human language. Fourthly, the Artificial Intelligence Robotics segment covers the combination of AI, machine learning, and engineering to create intelligent machines that can perform tasks autonomously. Fifthly, the Autonomous & Sensor Technology segment covers machines and systems that operate independently by using sensors, AI, and machine learning to respond to changes in their environment. Lastly, the Generative AI segment covers AI that involves creating models capable of generating new content, such as images, videos, and text, which are indistinguishable from content created by humans.

1.2. The Bulgarian context: AI adoption and digital landscape

Research into digital transformation in Bulgaria reveals a landscape of strong foundational digital infrastructure. 96.4% internet penetration among firms with 10 plus employees. The adoption of advanced digital technologies remains moderate. Recent statistics (NSI, 2024) show that 50.4% of firms maintain website, 21.7% use Enterprise Resource Planning (ERP) systems to manage business processes. 10.5% utilize Customer Relationship Management (CRM) systems to enhance customer relations. 17.5% employ paid cloud services. Notably, activities that form a foundation for AI implementation, such as analysis, e-invoice sending automation, are conducted by 21.9% and 15.8% of firms.

Against this backdrop, AI adoption represents an emerging frontier. Yordanova et al. (2025) reported that 3.6% of firms using AI technologies. This adoption rate is notably higher among larger companies (13.8%) compared to medium (10.0%) and small enterprises (5.5%). Additionally, Velichkov et al. (2024) concluded that 18% of companies that implemented EU projects also execute AI solutions.

Alongside adoption, significant attention is paid to data governance and user concerns. Trust among various AI applications, personal privacy and data security are the topics people mentioning in everyday life (ARC Fund, 2024). In 2023, 50.3% of individuals managed access to their personal data online. Measures included reading privacy policies (31.9%), restricting access to geographical location (21.8%), and limiting access to profiles on social networking sites (20.2%). These concerns highlight the importance of robust data protection frameworks in digital services to foster consumer trust. These findings on adoption rates, infrastructure, data practices, and user concerns collectively sketch the unique digital environment in which Bulgarian organizations operate, setting the stage for a critical analysis of the influencing factors specific to this context.

1.3. A synthetic framework: factors influencing AI adoption

Most dominant theories in studying accepting new technologies were Technology-Organization-Environment (TOE) framework, DOI theory, UTAUT, TAM, and others. A body of research has examined the challenges that need to be conquered to achieve widespread adoption of AI. Looking more into the AI challenges, there is a wealth of literature studying the factors driving or hindering the implementation of AI cases within organizations, regarding to technological, organizational, and environmental context. To critically synthesize this literature, the following subsections organized the key factors using the TOE framework, which provides a structured lens to analyze the technological, organizational, and environmental dimensions. This structured synthesis will then serve as a basis for discussing their specific relevance to the Bulgarian context outlined in Section 1.2.

1.3.1. Technological factors

Research highlights several technological attributes as critical determinants. Al Sheibani et al. (2018) investigated the impact of factors like relative advantage and compatibility on AI adoption. Similarly, Gupta et al. (2022) included factors such as relative advantage, complexity, and IT expertise, identifying that relative advantage and complexity significantly influence employees' behavioral intention to adopt AI in the Indian insurance industry. Nam et al. (2021) also highlighted relative advantage, complexity, and IT expertise as crucial technological factors. Baabdullah et al. (2021) focused on the importance of infrastructure in the adoption process, finding that infrastructure and awareness significantly affect AI acceptance, while technical competence does not. Technological competence within an organization, including IT infrastructure and employee skills, is another crucial factor. Li et al. (2024) revealed several key findings about the relationship between employees' use of AI and their learning from AI. Pan et al. (2023) identified AI system quality and perceived AI risk as critical factors affecting AI adoption in the hospitality industry.

1.3.2. Organizational factors

Organizational characteristics and resources are equally pivotal. Studies have consistently shown that top management support is a powerful determinant of AI adoption, as it provides strategic direction and resources necessary for implementing innovative projects (Cao et al., 2021). Furthermore, CEO's cognitive traits were studied by Aghdaie et al. (2020) including risk-taking, innovative, and self-efficacy and a supportive organizational culture can enhance AI adoption in SMEs. Organizational size also plays a role. For instance, large firms have more resources to overcome AI constraints. In contrast, Alsheibani et al. (2019) suggest that company size does not significantly impact AI usage. Financial readiness is also important, as noted by Gaafar & Allah (2020). They argued that firms with better financial capacity are more likely to adopt advanced AI technologies. Resistance by employees, often due to fears of job replacement by AI, is another significant organizational barrier that needs addressing, according to the findings of Vicsek et al. (2024) and Lestart & Djastuti (2020).

1.3.3. Environmental factors

The external environment exerts considerable pressure and provides support mechanisms for adoption. Competitive pressure, the threat of losing competitive advantage, is a strong motivator for AI adoption, as noted by Gupta et al. (2022) and Aboelmaged (2014). Regulatory support is another critical factor, with studies such as those by Pan et al. (2022) and Chen et al. (2023) showing that government policies and regulations can significantly influence AI adoption by creating a favorable environment. For instance, the EU's Artificial intelligence Act (AI Act), which came into force in August 1, 2024, aims to foster responsible AI development while addressing potential risks and to encourage broader AI adoption. Industry dynamics also play a role. Industries that are more technology-intensive or face higher competitive pressures are more likely to adopt AI, as discussed by Hu et al. (2012) and Abdullah & Fakieh (2020). Customer experience and service experience with AI are additional environmental factor that can influence adoption, particularly in customer-facing industries like hospitality, as noted by Nam et al. (2021). Ethical considerations, such as accountability and transparency, are increasingly recognized as necessary for AI readiness, especially in developing countries, as highlighted by Kulkarni et al. (2024).

1.4. Synthesis and application to Bulgaria's context

Having synthesized the key factors influencing AI adoption through the TOE framework, it is crucial to discuss their specific manifestations and interplay within the Bulgarian context. For instance, the relatively low AI adoption rates among Bulgarian SMEs, as reported by Yordanova et al. (2025), can be critically examined through the lens of organizational factors like financial readiness and technological factors such as perceived complexity and lack of IT expertise. The high internet penetration but low high-speed connection adoption might reflect underlying challenges in technological infrastructure, a key technological factor. The significant concerns over data privacy among Bulgarian users, as highlighted by nation statistics, directly intersect within the environmental factor of regulatory support (e.g. the EU's AI Act and GDPR) and the technological factor of perceived AI risk, potentially creating a unique barrier or driver for adoption that requires tailored strategies. Furthermore, the role of competitive pressure in a small, open economy like Bulgaria's may differ from that in larger markets, potentially making EU-wide competitive dynamics and support programs even more critical environmental factors. This contextualized analysis strengthens the theoretical contribution by moving beyond a generic list of factors to explain the specific dynamics at play in Bulgaria.

1.5. Research hypotheses

Based on the literature review, the study utilizes TOE framework for general guidance. The thesis of this study is that different groups of companies are characterized by different level of technical, organizational, and environmental readiness and adoption of AI applications. Specifically,

H1: Technological factors significantly influence the AI adoption readiness of Bulgarian firms.

H2: Organizational factors significantly influence the AI adoption readiness of Bulgarian firms.

H3: Environmental factors significantly influence the AI adoption readiness of Bulgarian firms.

2. Methodology

The main goal of this research is to uncover and analyze the factors that are related to AI readiness and adoption across different groups of companies in Bulgaria. Bulgarian firms are the target sample used in this study. The study adopts a survey method by using structured questionnaire. The questionnaire was developed based on the examples from the European enterprise survey on the use of technologies based on artificial intelligence (2020). The independent variables are measured at 4-point Likert scale. The questionnaire was distributed electronically over 6 months in Q4 2023 and Q1 2024, and we received 81 responses usable for analysis. Respondents are top management of the company, who have a better business vision in strategic management and possess the authority to make decisions. The study uses a mixed method of sampling to collect data. Mostly we used convenience sampling (interviewing during important industrial events) and snowball sampling (mainly in start-up communities), sending also emails to some companies. Data analysis was performed using SPSS Statistics version 25. First, descriptive statistics were computed to profile the characteristics of the sample. Subsequently, Exploratory Factor Analysis was conducted on the Likert-scale items to validate the underlying factor structure.

3. Results and discussion

3.1. Descriptive analysis

Firstly, the distribution of firms across different regions shows a concentration in the capital city (63%), with smaller proportions in regional centers, small towns, and villages. Ownership structure is predominantly autonomous (77.59%), indicating a strong inclination towards independent decision-making. In terms of company size, micro-enterprises constitute the majority (65.52%), with fewer large enterprises represented (12.07%). The size of the firm is a critical factor in AI adoption, as larger firms often have more resources to invest in advanced technologies. Decision-making processes in these firms vary, with the majority involving input from key stakeholders (46.55%).

Secondly, the data management practices of the surveyed firms reveal a reliance on database management system (46.9%) and a significant number still using Excel spreadsheets (29.6%) as a dominant method. This reliance on traditional tools may reflect a gap in technological infrastructure that could impact AI readiness. A considerable number of firms (58%) collect and store electronic data on operations and customers, which is a foundational step towards leveraging AI. However, there remains a significant portion of firms (22.2%) unsure about their data practices, which could impede AI adoption if data management is not adequately addressed. Skills gaps are notable, with a high demand for machine learning, big data management, and programming skills.

Thirdly, the study reveals that 60.87% of firms have experimented with AI, indicating a growing interest in the technology. However, only 18.5% have fully developed AI solution in-house, while the majority have either purchased ready-to-use software or modified existing systems. The presence of AI without clear knowledge of its acquisition method (11.1%).

3.2. Factor analysis

All items are subjected to varimax rotated principal components factor analysis. We extract with criterion of eigen value-greater-than-one five-factor solution, which explains 76.58% of variance. The retention decisions of each item were based on factor loadings greater than or equal to 0.50 and cross-loading with the other factors generally smaller than 0.35 (Igbaria et al., 1994). As suggested in the Table 1, retained item-to-factor loading is above 0.70. The Kaiser-Meyer-Olkin measure of sampling adequacy was 0.579 and the Bartlett's test of sphericity (Chi-square = 288.712) is found to be significant (Sig.=0.000). The diagonal entries of the anti-image correlation matrix values are greater than 0.50 (between 0.668 and 0.938), indicating acceptable correlations among the items. Reliability analysis revealed that four of the five factors demonstrated good internal consistency, with Cronbach's alpha coefficients above 0.70 benchmark (Hair et al., 2012). Factor 5 showed a marginally acceptable alpha of 0.632. Original seven-dimension variables are decreased to five factors (Table 1).

Table 1. Rotated factor matrix

Items	F1	F2	F3	F4	F5
AI application 7	0.855				
AI application 5	0.835				
AI application 3	0.785				
AI application 6	0.778				
AI application 2	0.705				
Ex-Obstacle 1		0.835			

Items	F1	F2	F3	F4	F5
Ex-Obstacle 4		0.803			
Ex-Obstacle 3		0.776			
Ex-Obstacle 2		0.754			
AI Concept 10			0.884		
AI Concept 8			0.812		
AI Concept 1			0.774		
Attitude 4 - Gain market position				0.941	
Attitude 3 - boost business performance				0.867	
Attitude 7 - Customer readiness				0.817	
Lack of internal data					0.790
Lack of public or external funding					0.745
Cronbach's Alpha	0.786	0.828	0.778	0.85	0.632
Eigenvalue	3.880	3.414	2.441	2.073	1.211
% of Variance	22.824	20.08	14.358	12.192	7.122
Total Variance explained	**76.58%**				

Source: Author

We name the F1 as AI adoption. Our starting point for defining F1 as AI adoption is to parse out whether or not enterprises are currently using these specific AI applications, given that Singla et al. (2025) defines AI adoption as the application of AI technologies in business strategies and operations. F1 contains five types of AI applications deployed in the firms currently such as: AI application 7 - Recommendation & personalization engines using AI to produce customized recommendations, via matching algorithms or information retrieval; AI application 5 - Forecasting, price optimization and decision-making using machines learning algorithms; AI application 3 - Fraud detection or risk analysis, also known as anomaly detection; AI application 6 - Process automation using AI, including warehouse automation or robotics process automation (RPA); AI application 2 - Visual diagnostics, face or image recognition, also known as computer vision.

We name the F2 as External obstacle. It includes four aspects in terms of: the need for new laws or regulation; liability for damage caused by artificial intelligence; reputational risks linked to using artificial intelligence; strict standards for data exchange (e.g., data protection laws). Government policy has been recognized as one of the factors that firms need to consider (Huang, 2018). as people concerns. Typical examples of legal issues are privacy, security, and government regulations. An example, Facebook's auto-tagging feature employs image recognition to identify your friend's face and tag them automatically. The social network uses ANN to recognize familiar faces in users' contact lists and facilitates automated tagging. But now Meta company has stopped using this AI tool.

We name the F3 as AI awareness. In alignment with the same research idea as AI adoption, we prepared ten AI concepts to test the awareness or understanding of these concepts among owner(s) of the company or employees in the organizations. Our factor analysis reveals that three concepts among ten were significant, which related to AI technology and its sub-field and its impact. Detailed descriptions include basic concepts and principles of artificial intelligence; machine learning and deep learning algorithms' impact of artificial intelligence on job market and employment. Awareness about AI among organizational stakeholders or people is their knowledge on AI, its benefits, and risks that are key factors in the voluntary use of system (Alsheikh & Bojei, 2014, p. 212; Baabdullah et al., 2021).

We name the F4 as Attitudes. Attitude towards AI explains the positive or negative feelings individuals have towards the AI technology (Cao et al., 2021). Anandarajan (2002) talked about the organizational leader or manager and studied the perception and behavior of leaders towards the adoption of new IT in the business process. In our study, attitudes emphasize the benefits of using AI and how organization perceived the customers' attitude of using AI. The study of Cao et al. (2021) found that the managers' attitudes towards AI are positively influenced by performance expectancy and effort expectancy, but negatively influenced by personal wellbeing concerns and perceived threat. Whitman et al., (2018) found that younger and less experienced participants believed that AI implementation could be helpful and improve their work by taking over their repetitive and administrative tasks. The position of employees at company revealed considerable distinctions between frontline roles and back-office roles in the study of Lestart & Djastuti (2020). The former is concerned that AI technologies will be able to replace their jobs; while the latter believed that human actions would still be required to conduct analysis procedures correctly and did not feel threatened by AI replacement. Therefore, this factor embodies the readiness on organizational level.

We name the F5 as IT Resources. It concludes two aspects namely data resource (lack of internal data), and financial resources (refer to lack of public or external funding). Using AI involves significant IT resources and knowledge (Ransbotham et al., 2017). Technological resources focus on computer hardware, data, and networking. Essentially, AI needs data, algorithms, and computing power. People generate data all the time, such as personal identity information data, social interaction data, consumer transaction data, etc. Financial readiness is also important, as noted by Gaafar & Allah (2020). They argued that firms with better financial capacity are more likely to adopt advanced AI technologies. Therefore, this factor contains partial technological readiness in data, and partial environmental readiness.

3.3. First cluster analysis

For the purpose of first cluster analysis, these five factors are transformed into new composite measures (Hair et al., 2012), calculated as a sum of the values of constitutive items, divided by maximum sum and multiplied by 100 (F1, F2, F3, F4, F5). Specifically, the hierarchical cluster analysis with the Ward's method is run to determine the number of clusters (Hair et al., 2012). We proceed with a four-cluster solution because it implies less heterogeneity than the other cluster solution (Hair et al., 2012). The non-hierarchical cluster analysis results in cluster size of 22, 12, 13, 6 cases respectively (Table 2). The difference in the variables means across four clusters are statistically significant.

However, F1 and F2 are not statistically significant, which were not further studied. FI (AI Adoption) refers to current use of AI applications in companies. We set this question as a window to mirror the technology capability of organizations in respect to the technological readiness dimension. F2 (External Obstacle) refers to regulatory, strict standards for data exchange, and reputation risk to AI adoption. Therefore, in this study these two factors cannot be taken into investigated both technological readiness and environmental readiness. Also, the subsequent cluster analysis was conducted on partial number of companies. This reduction is attributable to the heightened difficulty of the later survey questions, which led to a lower response rate and incomplete data from the remaining.

Next, the four clusters demonstrated distinct profiles characterized by significant variations in their AI awareness, attitudes, and perceived obstacles from data resources and financial resources. The ANOVA results (all $p<0.05$) confirm that these inter-cluster differences are statistically significant.

Table 2. Values of means of significant constructs by cluster

Constructs	Average scores of constructs by clusters				F	Sig.
Clusters	1	2	3	4		
F3. AI Awareness	2.5303	0.4722	1.8462	1.2222	23.854	0
F4. Attitudes	3.8788	4.1667	2.9231	1.7778	40.142	0
F5. IT Resources	1.7500	2.2083	2.7308	1.3333	3.435	0.025
Size of the clusters	22	12	13	6		

Source: Author

Cluster 1 (n=22) exhibits a moderate level of AI awareness coupled with the second-most positive attitudes towards AI. Their path is facilitated by facing relatively low obstacles, which suggests a practical and potentially successful adoption journey. Cluster 2 (n=12) shows a striking paradox. They report the lowest understanding level of AI among all clusters, yet they hold most positive attitudes. This unchecked optimism may be risky, because they face a moderate level of obstacles in aspect of data resource and financial resource that their low awareness could prevent them from effectively navigating. Cluster 3 (n=13) represents companies with a below-average understanding of AI, and only moderately positive attitudes. But they face the highest level of obstacles among the clusters. This indicates that while they are not entirely pessimistic about AI, the significant challenges they encounter may hinder their progress. This combination reflects their cautious stance may be a direct result of the significant barriers they face, potentially stalling their AI initiatives. Cluster 4 (n=6) has a relatively low understanding of AI, and also exhibits the lowest attitude towards AI. However, this group reports the fewest obstacles. This suggests that their disengagement stems not from external challenges but from a lack of interest or perceived relevance of AI to their operations.

3.4. Second cluster analysis

In the second cluster analysis, we used nonmetric variables (1) ownership, (2) area of country, (3) sector, (4) decision-making process, (5) size of company, (6) planning intensity (an index of AI applications targeted for employment in the subsequent 24 months), (7) innovation intensity, and tested their relationships by a cross-tabulation. We observed that only planning intensity is vital to AI adoption (Sig.=0.005). Given that AI awareness, Attitudes and IT resources influence the behavioral intention and actual use in AI practice, we further explored their reflection on AI adoption (the current use of 10 AI applications) by the second cluster analysis. Specifically, we used the K-means clustering algorithm of SPSS for 10 iterations with four variables (dummy variable "use-not use", intensity of use, intensity of planning, and deeper understanding variables). Four cluster centres were identified, and ANOVA analysis was performed. The result shows that the clustering centres demonstrate the mean values of different companies on AI understanding, Intensity of use and Intensity of planning. On the other hand, the ANOVA analysis results shows that the significance level of all the variables is less than 0.05, which indicates that there is a significant difference between different clusters on these variables (Table 3).

Table 3. Means of the second cluster analysis

Construct	Mean of constructs by clusters				F	Sig.
Cluster	1	2	3	4		
In depth understanding	7,06	1,73	1,52	2,32	49,879	0,000
Usage Intensity	1,11	6,45	0,52	1,32	78,871	0,000
Planning Intensions	2,72	0,91	0,36	4,89	52,522	0,000
Usage (no/yes)	0,56	1	0,33	0,74	7,328	0,000

Source: Author

After analyzing the means of various other variables per cluster we find out that the proper profiling of the clusters would be associated with the following descriptions and names (Usage intensity and Planning intensity). Figure 1 below presents four categories of AI practice among surveyed Bulgarian firms.

Cluster 1, with 22% of the cases comprise of companies which claim a very high level of understanding of many different aspects of AI (variable in-depth understanding), however with significantly lower usage intensity and even low AI experimentation history. The discrepancy between understanding and usage is the highest in this group, which leads to the name “wannabe” companies. They have moderate plans to adopt AI in the future, but are not yet ready in terms of budget, planning and organizational culture. Cluster 2 comprises 14% of studied companies, which have the highest usage intensity. The companies are significantly more innovative (index = 0,3535) compared with the other groups, have a dedicated budget for AI implementation, a governance structure and organizational culture enabling the adoption of AI. In all characteristics the companies in this cluster demonstrate that they are true leaders, so we call them “leaders”. Cluster 3 comprises of 41% companies exhibiting both the lowest AI usage and AI planning intensity. They are also the least innovative companies (index = 0.1566), significantly below all other clusters. Even in cases of companies suggesting they are planning to implement AI they seldom have dedicated budget and never a governance scheme for that. Naturally we call them “laggards”. The laggards, similar to the “wannabes” tend to have similar responses to the questions about AI understanding. Cluster 4 comprises 23% of companies with the highest AI planning intensity. Their self-perception about AI seems more realistic, following just after the leaders (the coefficient (in depth understanding/usage intensity). They have the highest ratio of experimentation, most probably as part of their decision-making and planning activities on how to implement AI. We call these companies “catch-uppers”.

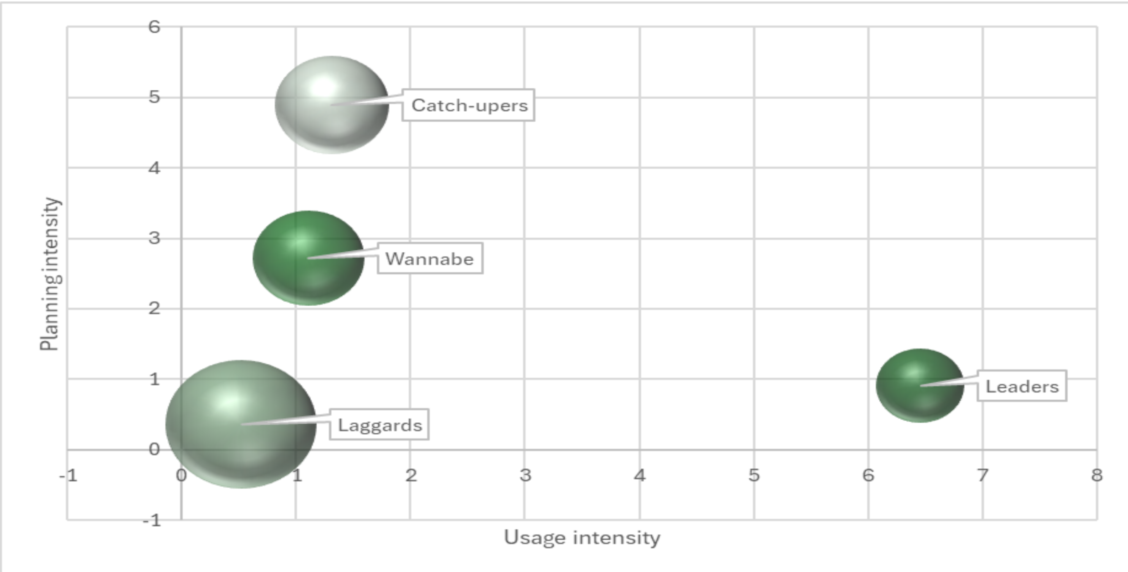

Figure 1 Four categories of AI practice.

Source: Author

Conclusions

This study aims to uncover the factors that are related to AI readiness and adoption across different groups of companies in Bulgaria. For this reason, we used data from 81 respondents. The data were processed by factor analysis and two cluster analyses.

The findings validate and extend the TOE framework by identifying the most salient factors in the Bulgarian context. In the technological dimension this is lack of internal data, in the organizational dimension this are AI awareness and attitude, and in the environmental dimension this is external funding. The study makes a distinct empirical contribution by defining a typology of four player types in the AI landscape - leader, laggards, catch-upper, and wannabe - characterized by current intensity of AI use and future adoption. Management leaders can better shape the awareness and attitude on AI itself, and to offer tailored support services to different types of companies. The study provides insights to businesses, organizations, policy-makers when making strategic decisions regarding resource allocation, governance structure, and policy development related to AI.

This study acknowledges its exploratory nature due to sample size, while this limits the generalizability of the findings to a broader population of Bulgarian firms. While these methods were practical for accessing a hard-to-reach population like top managers, they introduce the potential for selection bias, as the sample may not be fully representative of all Bulgarian firms. For instance, participants from industrial events or startup communities might be more innovative or AI-aware than the average firm. The field of AI is constantly evolving, which can make it challenging for researchers to keep up with the latest technologies, trends, and adoption pattern. Moreover, owing to the complexity of AI, it is difficult to generalize findings across all AI technologies.

This study also provides a present avenue for future research in emerging economies. Firstly, Focus on impact of demographic characteristics of companies on AI adoption. Secondly, exploring the effective AI promotion strategies tailor to different groups. Since groups differ in AI awareness, attitudes, data, funding, and actual usage of AI, they may require distinct strategies to enhance their technological adoption level. Moreover, developing dynamic models to simulate the progress and transitions of different groups along the technology adoption pathway.

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