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AVTOREFERAT OF DISSERTATION WORK

TOPIC: ARTIFICIAL INTELLIGENCE READINESS

AND ADOPTION IN SMEs

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CONTENT OF AVTOREFERAT

I. GENERAL CHARACTERISTICS OF THE THESIS

This research investigated the critical and rapidly evolving field of Artificial Intelligence (AI). AI is viewed as an essential business solution and foundation capability for organizations of all sizes (Chui and Francisco, 2017). Also, AI that has seen significant growth and impact across various industries. The selection of this topic is **motivated** by both scientific curiosity and practical importance, since AI continues to reshape business management, industry practices, and organizational strategies.

The **objective of this scientific work** is to explore and analyse the factors related to AI readiness and adoption among companies in Bulgaria. This study aims to uncover the key enablers and barriers to integrating AI within organizational structures and to assess how these factors impact operational performance.

The **object of the study** is Bulgarian companies across various industries, with a focus on their adoption and integration of AI technologies.

The **subject of the research** is the AI readiness in the technological, organizational, and environmental context and adoption of AI applications within firms. Specifically, the thesis of this study is that different groups of companies are characterized by different level of technical, organisational, and environmental readiness and adoption of AI applications. Accordingly, we formulate **Hypothesis** as follows:

H1: Different groups of companies are characterized by different level of technical readiness and adoption of AI applications;

H2: Different groups of companies are characterized by different level of organizational readiness and adoption of AI applications;

H3: Different groups of companies are characterized by different level of environmental readiness and adoption of AI applications and adoption of AI applications.

The **methodology** of the study employs a mixed-methods approach, combining a scoping literature review and a quantitative survey. The survey, distributed among Bulgarian companies, gathers data on technological, organizational, and environmental factors related to AI readiness and adoption. Factor analysis and two cluster analyses are used to identify patterns and group companies based on their readiness and adoption levels.

Applicability of Results. The findings of this research are applicable in guiding Bulgarian companies and policymakers in developing strategies to enhance AI readiness and adoption. The results can also inform future research on AI integration in other regions or industries.

The study has the following **limitations.** First, this study relies on specific groups or organizations for data collection, which potentially limiting the generalizability of findings. Second point is 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.

The described goals and tasks provide an overview of the **structure of the thesis.** The dissertation is composed of an introduction, two chapters, a conclusion, a list of references, and appendices.

II. STRUCTURE OF THE DISSERTATION

Chapter one provides a literature review on the topic of Artificial Intelligence (AI). An overview of the main definitions of AI, its components, and applications across different industries is presented. The current state of AI in Bulgaria is analysed adopting the perspective of PEST analysis. The theoretical foundations for accepting new technologies are outlined, along with the factors influencing readiness and/or adoption of AI. As a result, a research model with hypotheses, based on the factors under the dimensions of technological, organizational, and environmental framework is developed to explore the adoption of AI.

Chapter two describes the empirical study conducted on the factors related to the readiness and adoption of AI. It includes a description of the survey design, data analysis, and results, as well as factor analysis and cluster analysis. The chapter concludes with a discussion to verify the proposed hypotheses and models.

Contents of Dissertation Work

List of Tables

List of Figures

III. BRIEF DESCRIPTION OF THE DISSERTATION WORK

INTRODUCTION

The introduction of dissertation presents the relevance and significance of the problem, reasons for choosing the topic, aims and objectives of the research, methodology of the research, results and applicability of the research limitations of the research, which are set out in the first chapter of the present abstract. The introduction ends with a brief presentation of the structure of the dissertation.

1. CHAPTER ONE: THEORETICAL PARAMETERS OF THE RESEARCH

1.1. Artificial Intelligence - definitions, components, applications

AI is emphasized as a data-driven technology. Kaplan & Heanlein (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.

From the perspective of management, AI is another empowerment of machines by humans. A 2024 McKinsey report[1] reveals that 72% of respondents' organization have adopted AI and 50% of respondents stated that AI has been used in more parts of business of their organizations.

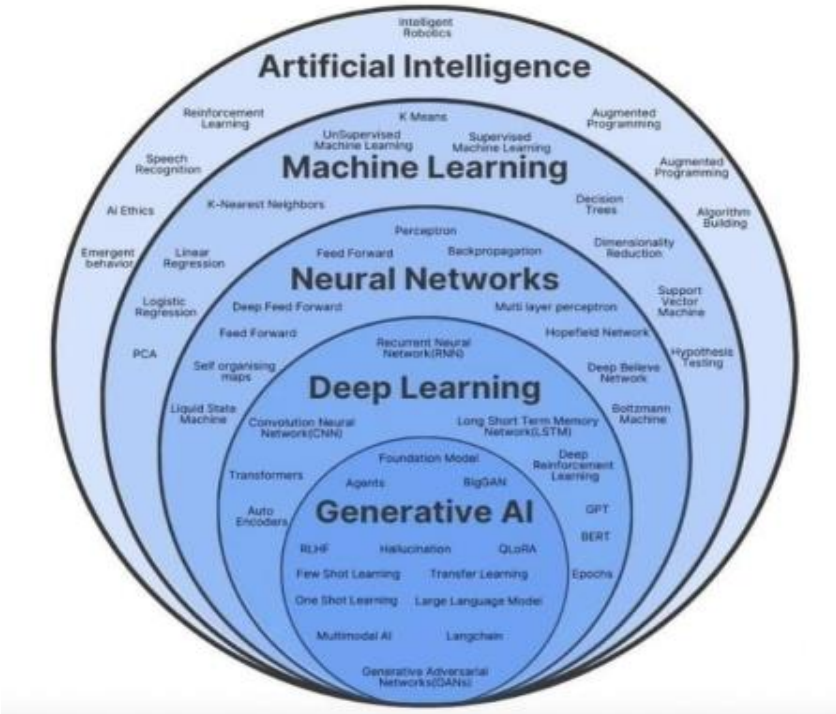
Analytics Vldhya[2], visually represented the hierarchical relationship (Figure 1) between various subfields and techniques within the domain of artificial intelligence (AI).

In the outer circle of AI, various types of algorithms serve as the fundamental building blocks, each designed to handle specific tasks and challenges. The second circle is named Machine Learning. Machine Learning is a field of study in artificial intelligence concerned with the development and study of statistical

1 https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai
2 https://www.facebook.com/photo/?fbid=940469631417721&set=a.506681458129876

algorithms that can learn from data and generalize to unseen data, and thus perform tasks without explicit instructions (Koza et al., 1996).

Figure 1. AI components



Source: Analystics Vldhya (2024)

The third circle is called Artificial Neural Network. Artificial Neural Network is one type of model for machine learning. It is a model inspired by the structure and function of biological neural networks in animal brains (Mahesh, 2018). The fourth circle is called Deep Learning. Deep learning has received much attention in the last decade, partly because of its ability to deal satisfactorily with data that proved difficult for other machines learning models. Deep learning is a class of machine learning algorithms that uses multiple layers to progressively extract higher-level features from the raw input (Deng, 2014). Innermost circle is Generative AI. Generative AI refers to a class of machine learning technologies that can generate new content—such as text, images, music, or video—by analysing patterns in existing data. The emergence of generative AI has attracted significant attention since Open AI released the free version 3.5 of ChatGPT[3] in November 2022. As reported, one billion people registered in five days.

According to the AI index report[4], in 2023, a total of 149 foundation models were released, more than double the amount released in 2022. Of these newly released models, 65.7% were open source, compared to only 44.4% in 2022 and 33.3% in 2021. Global private AI investment has fallen for the second year in a row, though less than the sharp decrease from 2021 to 2022. However, the number of newly funded AI companies increases, up to 40.6% from the previous year.

The global artificial intelligence market size was estimated at USD 196.63 billion in 2034 and is projected to grow at a compound annual growth rate of 36.6% from 2024 to 2030, according to the data discovered by Grandviewsearch[5]. As statista[6] suggests, the AI market is structured into six markets based on the technology. Firstly, the computer vision market covers applications that enable computers to interpret and understand digital images and video data. Secondly, the machine learning market covers the use of algorithms to enable computer systems to learn from data. Thirdly, the natural language processing market covers applications that enable computers to understand, interpret, and generate human language. Fourthly, the artificial intelligence robotics market covers the combination of AI, machine learning, and engineering to create intelligent machines that can perform tasks autonomously. Fifthly, the autonomous & sensor technology market 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 market 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.

3 https://en.wikipedia.org/wiki/ChatGPT
4 https://aiindex.stanford.edu/wp-content/uploads/2024/04/HAI_2024_AI-Index-Report.pdf
5 https://www.grandviewresearch.com/industry-analysis/artificial-intelligence-ai-market
6 https://www.statista.com/outlook/tmo/artificial-intelligence/worldwide

Manufacturing is a significant application area for AI technology. By introducing AI, the manufacturing sector has made substantial progress in production automation, quality control, and supply chain management. For example, machines learning algorithms are used to predict equipment failures and optimize production processes, significantly improving efficiency and product quality. The finance sector is also at the forefront of AI adoption. AI technology is widely used in risk management, customer service, market forecasting, and fraud detection. Notably, AI enhances efficiency and accuracy in algorithmic trading and robo-advisory services. In healthcare, AI is applied in disease diagnosis, personalized treatment plans, and drug development. For instance, image recognition technology excels in assisting doctors with disease diagnosis, and AI algorithms accelerate the screening and evaluation of potential drugs during new drug development. AI technology in retail is primarily used for customer relationship management, sale forecasting, and supply chain optimization.

By analysing customer behavior data, retailers can conduct more precise marketing, improving customer satisfaction and sales performance. The transportation industry is actively adopting AI technology to enhance operational efficiency and safety. Autonomous driving technology, intelligent traffic management systems, and logistics optimization algorithms are typical applications of AI in this field. In the education sector, AI is being used to personalize learning experiences, automate administrative tasks, and provide intelligent tutoring systems. AI-driven adaptive learning platforms can tailor educational content to meet the needs of individual students, improving learning outcomes. Additionally, AI tools are assisting educators in grading, attendance tracking, and proving insight into student performance.

The service industry benefits from AI through enhanced customer service, chatbots, and predictive analytics. AI-powered chatbots and virtual assistants provide 24/7 customer support, handle inquiries, and resolve issues efficiently.

Predictive analytics help business participant customer needs, personalize services, and improve customer satisfaction. In human resources, AI is transforming recruitment, employee engagement, and performance management. AI algorithms screen resumes, assess candidates, and predict employee retention. Additionally, AI-driven tools facilitate employee training, development, and performance evaluation, ensuring a more effective and unbiased HR process. The public sector is leveraging AI to improve public services, enhance decision-making and streamline operations. AI applications in public sector include predictive policing, smart city initiatives, and public health monitoring. By analysing large datasets, AI helps government agencies identify trends, allocate resources efficiently, and provide better service to citizens.

1.2. Current AI Landscape in Bulgaria

AI adoption in Bulgaria is growing, with 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%). AI applications mainly focus on process automation, customer service enhancement, and predictive analytics, driving efficiency and innovation across various sectors.

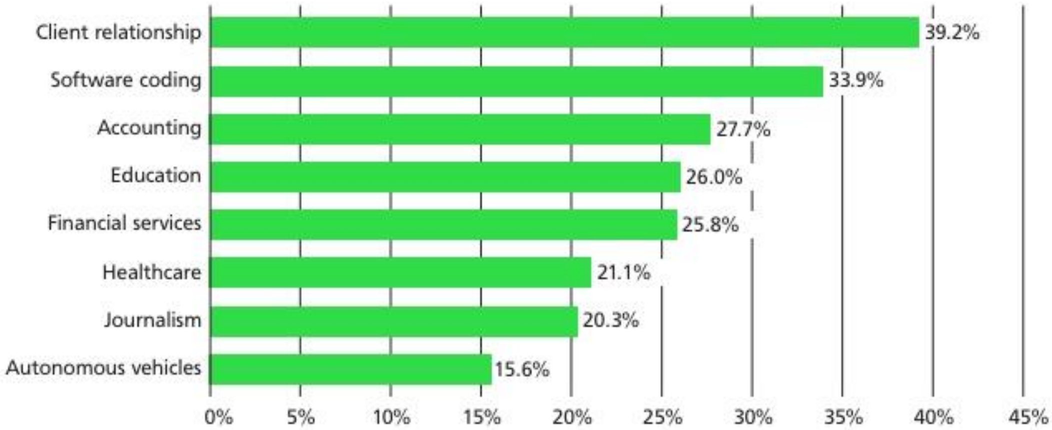
In political context. Bulgarian institute INSAIT is driving significant AI advancements in Bulgaria, marked by the launch of BgGPT[7] on January 15, 2024. The vision for Bulgaria's AI development by 2030 aims to build scientific, expert, and business capacities, to enhance education, to support research and innovation, and to establish an ethical regulatory framework, in align with the EU's digital transformation strategy.

In economic context. In 2022, 15.1% of Bulgarian enterprises sold goods or services online, accounting for 6.3% of their total turnover. In 2023, 45.2% of Bulgarians made online purchases, mainly clothing, accomodation, and cosmetics.

[7] https://bggpt.ai/

In social context. Trust in AI varies (Table 2), with high trust in automated call centres (39.2%) and lower trust in healthcare, journalism, and autonomous vehicles. About 21% of Bulgarians express concerns about job loss due to AI. Privacy and data protection are major concerns, with 50.3% managing their personal data online.

Figure 2. Trust in the use of AI by application area



Source: Author, Innovation.bg 2023, Information, Communication, and Information Technology, p.65

In technological context. Internet penetration in Bulgarian firms is high, with 96.3% of companies employing more than ten people having internet access. 38% of companies use platforms like Facebook, LinkedIn, and YouTube to enhance their online presence. In 2023, 21.7% of enterprises used Enterprise Resource Planning (ERP) systems to manage business processes, while Customer Relationship Management (CRM) systems were utilized by 10.5% of companies to enhance customer relations. Business Intelligence (BI) software was adopted by 4.2% of businesses for data-driven decision-making. The growing integration of these technologies indicates a positive trajectory towards digital transformation, essential for leveraging AI effectively. In 2023, 21.9% of companies performed data analytics, with larger enterprises more likely to engage in this activity. Data from transaction records, customer information, and government open data are the main sources for analytics. Businesses that preferred to have data analysed by their own employees accounted for 17.6%, while 7.6% outsourced this activity.

Several Bulgarian start-ups are at the forefront of integrating AI into their products and services.

1.3. Readiness and Adoption of AI

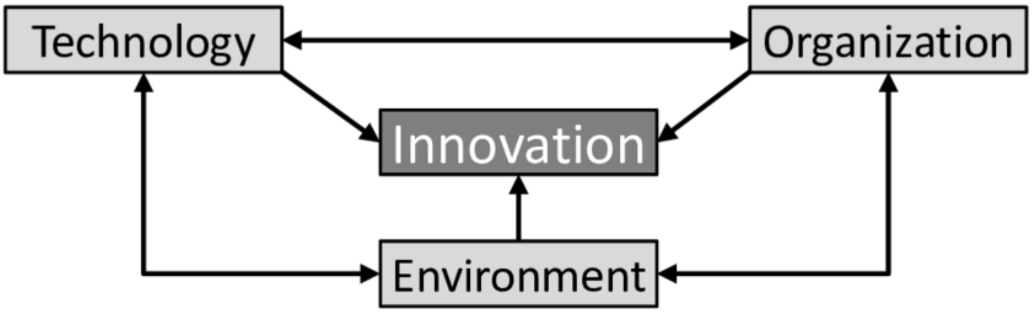
Readiness in the context of this paper is defined as preparedness at the organizational level for the intention to adopt AI. AI adoption in the context of this paper is defined as the actual usage of AI applications in the firms, instead of the intention to adopt AI. Lewin and Grabbe (1945) argued that people will resist changes if they are not ready for it. ORC theory suggests that achieving a high level of innovation adoption depends on the level of readiness.

1.4. Theorical foundations for accepting new technologies

Technology-Organization-Environment (TOE) framework is proposed by Tornatzk and Fleischer in 1990. It is a comprehensive model for understanding the factors that influence the adoption and implementation of technological innovations within organizations. This framework (as shown in the Figure 3) highlights several key aspects that are crucial for achieving successful technology adoption.

Firstly, the TOE framework identifies three primary contexts that influence technological adoption: technological, organizational, and environmental. The technological context refers to the internal and external technologies relevant to the organization, encompassing both existing technologies and new innovations. This context considers the perceived benefits, compatibility, and complexity of the technology, which affect its adoption

Figure 3 TOE framework



Source: Tornatzk & Fleischer, 1990

Secondly, the organizational context includes the internal characteristics of the organization that impact technological adoption. This involves the organization's size, structure, and resources, as well as the degree of formalization and centralization. Organizational readiness, which encompasses the availability of resources, employee expertise, and management support, is a critical factor in the adoption process. Companies need to align their technological strategies with their organizational goals and capabilities to facilitate successful implementation.

Thirdly, the environmental context encompasses the external factors that influence an organization's decision to adopt new technologies. These factors include the industry characteristics, market dynamics, competition, regulatory environment, and relationships with external stakeholders such as suppliers and customers. The pressure to stay competitive and comply with regulatory requirements can significantly drive the adoption of technological innovations.

1.5. Factors related to readiness and/or adoption of AI

In this study, we summarize six research papers that established their work on the basis of TOE framework. They reflected various perspectives on the influences on the AI adoption.

AlSheibani et al. (2018) investigated the impact of serval factors on AI adoption, with focus on the technological dimensions of relative advantage and compatibility. They also explored organizational aspects such as top management support, resources, and company size. Meanwhile, they considered environmental factors like regulatory support and competitive pressure.

Gupta et al. (2022) examined a broad range of factors, including technological aspects such as relative advantages, complexity, IT expertise, as well as regulatory support and competitive pressure. They included top management support, technological competence, and financial readiness in the organizational aspects. In terms of environmental one, they considered market dynamics, regulatory support, and competitive pressure. Their study found that in the Indian insurance industry, both technological and environmental factors significantly influence employees' behavioral intention to adopt AI-enabled applications. Specially, in the technological context, relative advantage and complexity significantly predict employees' behavioral intention. In the environmental context, market dynamics, regulatory support, and competitive pressure are significant predictors of behavioral intention. However, within organizational dimension, only top management and financial readiness were significantly associated with the behavioural intention to adopt AI. Technical competencies did not have a significant impact on AI adoption.

Nam et al. (2021) pointed out technological factors like relative advantage, complexity, and IT expertise. They covered financial readiness and employee resistance under the organizational dimension, and took customer experience and service experience with AI into consideration regarding environmental aspect. Their study examined the factors influencing the adoption of AI and robotics in the hotel industry, specifically focusing on Dubai-based hotels. Their finding highlighted that market position and customer were more influential than other factors like internal IT expertise, competition, and legal issues.

Baabdullah et al. (2021) looked at the AI trend in Middle East and target 392 SMEs in B2B business line. They concentrated on technological factor of infrastructure, the organizational factor of employee resistance, and the environmental factors such as service experience with AI. Their investigation has two contributions. Firstly, in terms of readiness for AI, they concluded that infrastructure and awareness had a significant impact on AI acceptance, while technicality did not. Secondly, technology road mapping and attitude significantly influence acceptance of AI practice. They also found that regarding the AI impact, it positively affects AI-enabled relational governance, performance, and AI-based business customer interaction for SMEs.

Pan et al. (2022) addressed technological dimension including relative advantages, complexity, and AI system quality. In the organizational dimension, they examined technological competence. Their environmental analysis included regulatory support, competitive pressure, and industry. They surveyed 297 Chinese companies in human resource management sector. The results suggested that the companies' perceived complexity towards AI was an obstacle for AI adoption; on the country, technology competence and regulatory support were drivers for AI adoption. However, the characteristic of AI technology-relative advantage, company size, and industry have no great impact on AI usage. Additionally, they found that transaction cost played a moderate role on the influential power of technological complexity and technology competence of company.

1.5.1. Technological dimension

Technological dimension in the TOE framework pertain to software and hardware technologies available inside or outside the organization that facilitate the adoption of AI practices. Various studies have explored different aspects of technological factors.

AlSheibani 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. Pan et al. (2023) identified AI system quality and perceived AI risk as critical factors affecting AI adoption in the hospitality industry. Yadav & Kapoor (2023) reiterated that AI complexity can hinder adoption, but technological competence and regulatory support are enablers.

1.5.2. Organizational dimension

Organizational dimension encompasses elements such as top management support, company size, technological competence, financial readiness, and employee resistance.

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. Furthermore, CEO's cognitive traits were studied by Aghdaie et al. (2019) 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. On the country, Alsheibani et al. (2019) suggest that company size does not significantly impact AI usage.

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. Firstly, the frequency of using AI among employees enhances their ability to learn from AI. Additionally, perceived enjoyment of using AI positively influence their learning process. This enjoyment also moderates the effect of AI usage frequency on learning, further enhancing its impact. Furthermore, the complexity of tasks positively affects employees' learning from AI and amplifies the positive impact of AI usage frequency on learning. Finally, there is a significant three-way interaction between AI usage frequency, perceived enjoyment, and task-related complexity, all contributing to employees' learning from AI. Similarly, Tursunbayeva et al. (2024) proposed strategies like AI training programs and knowledge-sharing platforms to enhance employees' AI-related skills, thereby maximizing AI benefits.

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 Nem et al. (2022) and Lestart & Djastuti (2020).

1.5.3. Environmental dimension

Environmental dimensions include factors like market dynamics, regulatory support, competitive pressure, and industry-specific conditions.

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). Regulaory 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 favourable 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 Hsu et al. (2006) 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).

In addition, there are some *debates* on the different groups of company in respect to the AI adoption. For example:

Debate One - *AI Maturity of Companies.* Neumann et al. (2022) examines how the importance of factors within TOE framework shifts across companies with different levels of AI maturity. It identified three groups. The first group with low AI maturity. It focuses on organizational factors, especially administrative issues, with technical factors being less important. The main concern is implementing basic AI technologies like conversational agents, often relying on motivated staff and external partners. The second group with intermediate AI maturity. It emphasizes technological factors as AI project become more complex. Strategic management, internal knowledge, and resource allocation become critical, while dependence on external partners reduced. The third group with high AI maturity. Organizations have significant internal resources for AI but still require top management support and collaboration. Technological factors remain crucial, with growing focus on AI diffusion and potential organizational conflicts. Environmental factors like ethics may also become important.

Debate Two - *Type of Companies.* As AI applications begin to address core business functions, the proportion of internal implementation increases, and the customer perspective gains importance. More AI-experienced organizations may be regarded as inspiring early adopters for other public organizations. State-owned enterprises may play a significant role in this, as they often have more innovative resources than other public organizations and can develop complex AI solutions in-house. However, as AI becomes more widespread within organizations, resistance may increase.

Debate Three - Size of Companies. Alexandre & Blanckaert (2020) indicated that relationship between company size and the adoption of AI in the business consultancy industry. The author highlighted that smaller firms face significant challenges in defining and implementing AI technology; whereas lager firms have the internal resources and capabilities to develop and utilize AI for decision-making. The implementation of AI is strongly correlated with the company size. The reason is that larger companies more frequently have the opportunities and means to adopt AI programs. In contrast, smaller companies find it much harder to implement AI due to limited resources and capabilities. Therefore, the author addressed the critical role that company size plays in the ability to successful adopt AI technologies.

1.6. Research model and hypothesis development

In accordance with the points mentioned in section 1.5, this paper is utilizing TOE framework for general guidance. Here the Figure 4 presents the elements of AI readiness and AI adoption model and identifies the constructs and variables.

Figure 4. Conceptual Framework

Adoption by Different Groups of Companies		
AI Readiness in Technological Context	AI Readiness in Organizational Context	AI Readiness in Environmental Context

Source: Author

Accordingly, we formulate Hypothesis as follows:

H1: Different groups of companies are characterized by different level of technical readiness and adoption of AI applications

H2: Different groups of companies are characterized by different level of organizational readiness and adoption of AI applications

H3: Different groups of companies are characterized by different level of environmental readiness and adoption of AI applications and adoption of AI applications

2. CHAPTER TWO: ANALYSIS OF THE RESULTS OF THE RESEARCH

Our study used an online Lime survey distributed electronically over 6 months in Q4 2023 and Q1 2024, and we received a total of 223 responses, however many of them were not usable as the majority of them had only the first section of questions filled out. After data cleaning we found out that 81 responses usable for analysis, out of which 50 full responses (all questions answered).

This study adopts a survey method by using structured questionnaire. Bulgarian firms were the sample population used in this study. Since this study seeks to examine the factors influencing the adoption of AI applications among firms, the expected respondents are owners or high management level of the company. They usually have a better business vision in strategic management and possess the authority to make decisions.

2.1. Survey Design

The questionnaire was developed based on the examples from the European enterprise survey on the use of technologies based on artificial intelligence (2020). It consists of five sections: section one examines the understanding of AI concept and AI application, as well as the innovation intensity of firms. Section two assesses the adoption of AI applications and challenges faced by companies. In section three, the questions are set to predict the future adoption of AI applications, and section four examines the demographic factors of the participated companies and position level of respondents at the company. This questionnaire has a total of 34 questions. For the details of the questionnaire, the full content is well described in the Appendix 1. For all independent variables in this study, the response format has five types, including single choice, 4-point Likert scale, also 5-point Likert scale, and 10-point scale and text. Here we would like to detail the measurement of variables in our study in accordance with TOE framework.

2.2. Data analysis and results

2.2.1 Descriptive statistics

This study provides a detailed look into the AI adoption landscape in Bulgarian firms, revealing a mix of organizational characteristics, technological capabilities, and approaches to AI implementation. With a sample size of 81 firms from a distributed 156 questionnaires, the insights gathered offer a nuanced understanding of AI readiness and adoption among Bulgarian businesses. This discussion synthesizes the data of descriptive analysis from three key areas: company characteristics, data management and skills, and AI implementation methods.

Firstly, the distribution of firms across different regions shows a concentration in the capital city (63%), with smaller proportions in regional centres, 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%).

2.2.2 Reliability results of variables or constructs

Table 6 presents the results of reliability analyses for seven scales. AI adoption scale measures the extent to which respondents' companies have adopted 10 specific AI applications. The overall reliability of this scale is 0.844. Understanding scale measures to the extent to which respondents' familiar with 10 concepts related to AI. The overall reliability of the scale is 0.834. External obstacle scale measures the 8 aspects from the context outside of the company such as regulatory, access to data, external funding, AI risk, and trust. The overall reliability of this scale is 0.879. Internal obstacle scale measures 7 aspects faced by companies when adopting AI applications such as cost, skills, IT infrastructure. The overall reliability of the scale is 0.865. Attitude (towards AI) scale measures 6 aspects from the angles of employees, owner(s), customers. The overall reliability of the scale is 0.853. Organizational culture scale measures continuous learning and development, innovation and experimentation, risk-taking and failure tolerance, data-driven decision-making. The overall reliability of the scale is 0.825. Technological capacity scale includes IT infrastructure, Access to high-speed internet connectivity, Sufficient computing power, Technical skills and knowledge among your employees, Support for AI adoption among your leadership team. The overall reliability of the scale is 0.833.

Table 1. Reliability Statistics

Scale	Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
AI Adoption	0.844	0.843	10
Understanding	0.834	0.834	10
External Obstacles	0.879	0.879	8
Internal Obstacles	0.865	0.867	7
Attitude	0.853	0.857	6
Organizational culture	0.825	0.827	4
Technological Capacity	0.833	0.886	5

Source: Author

All these seven scales exhibit Cronbach's Alpha coefficients above 0.7. These results suggest that the measurement of the scales in the questionnaire are stable and consistent. They showed a good to excellent internal consistency and can be used for the next step such as factor analysis and cluster analysis.

2.3. Factor analysis

Factor analysis is a multivariate method used to study the internal structure among observed variables (i.e., original variables) by extracting latent variables (i.e., factors) to explain the correlation among the variables. Its main purpose is to describe the main characteristics of the data through a few factors, thereby simplifying the data structure and reducing data dimensionality.

Using factor analysis to conduct information condensation research, we first analyse whether the research data is suitable for factor analysis. A KMO value close to 1 indicates that factor analysis is appropriate; generally, a KMO value greater than 0.6 is acceptable. A significant Bartlett's Test of Sphericity (p-value < 0.05) suggests that the data is suitable for data analysis.

Next, we check whether the analysis items need to be adjusted. When factor analysis is performed to condense factors, it usually goes through multiple repeated circles, deletes unreasonable items, and repeats the circle many times to finally get a reasonable result.

All items were subjected to varimax rotated principal components factor analysis. When extracting with criterion of eigen value-greater-than-one, five-factor solution, which explained 76.58% of variance, was derived. 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, Iivari, & Marage, 1995). The remaining items were retested with factor and reliability analysis, which resulted in a five-factor solution shown in Table 7. Most item-to-factor loading is above 0.70, expect one item with a value of 0.519. Most of the factors have Cronbach's alpha value above 0.70, except one factor has a value of 0.632, which is close to the recommended threshold (Hair et al., 2010). These numbers of values present a good consistency of measures.

Table 2. Rotated Component Matrix [a]

	Component				
	1	**2**	**3**	**4**	**5**
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			
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**				

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 6 iterations.

Source: Author

The Kaiser-Meyer-Olkin measure of sampling adequacy was 0.579 (close to 0.6) and the Bartlett's test of sphericity (Chi-square = 288.712) was found to be significant (Sig.=0.000). The diagonal entries of the anti-image correlation matrix values were greater than 0.50 (between 0.668 and 0.938), indicating sufficient correlations among the items. Original seven-dimension variables were decreased to five dimensions.

We name the Factor 1 as *AI adoption*. It contains five types of AI applications deployed in the firms currently such as: AI application 7 - Recommendation & personalization engines using artificial intelligence 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 artificial intelligence, including warehouse automation or robotics process automation (RPA); AI application 2 - Visual diagnostics, face or image recognition, also known as computer vision.

Our starting point for defining Factor 1 as *AI adoption* is to parse out whether or not enterprises are currently using these specific AI applications, given that McKinsey[8] defines AI adoption as the application of AI technologies in business strategies and operations to achieve optimization and strategic goals. Their reports emphasize the practical applications of AI across various business functions.

We name the Factor 2 as *Regulatory issue*. It includes 4 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 (Hung, 2014). as people concerns. Typical examples of legal issues are privacy, security, and government regulations.

We name the Factor 3 as *AI awareness. A*wareness about AI among organizational stakeholders or people that their knowledge about AI, its benefits, and risks that are key factors in the voluntary use of system (Alsheikh & Bojei, 2014, p.212; Baabdullah et al., 2021). Therefore, this factor embodies organizational readiness.

In align with the same research idea as AI adoption, we prepared 10 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.

[8] https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai

The Factor four revels the *Attitudes* towards AI. Attitude explains the positive or negative feelings individuals have towards the AI technology (Cao et al., 2021). Anandarajan et al (2002) talked about the organizational leader or manager and studied the perception and behaviour of leaders towards the adoption of new IT in the business process. Therefore, this factor embodies organizational readiness.

In our study, attitudes emphasize the benefits of using AI and how organization perceived the customers' attitude of using AI. For example, you believe your company will probably gain market positions because of AI; You believe AI would boost your business performance; Your customers are ready to use AI-enabled interface with your company.

In the study of Cao et al. (2021) 269 managers from medium and large organizations in UK were surveyed. They found that their 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., (2023) 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.

The Factor five talks about *Obstacles*. 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. On the other hand, 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. According to Rogers (2003), technological resources include prior technological infrastructure, experience, and knowledge employed to support the implementation of innovation without additional investment. Therefore, this factor contains partial technological readiness in data, and partial environmental readiness.

2.4. First Cluster analysis

Commonly, cluster analysis is used to divide target samples into several sub-groups with distinct characteristics. Samples in the same group have great similarities, while samples in different groups have great differences.

For the purpose of cluster analysis, these five factors are transformed into new composite measures (Hair et al., 2010), calculated as a sum of the values of constitutive items, divided by maximum sum and multiplied by 100. The same way the other four factors, which are used to access the cluster predictive validity, are calculated (F1, F2, F3, F4, F5).

Two cluster analyses are conducted - hierarchical and non-hierarchical. The hierarchical cluster analysis with the Ward's method is run to determine the number of clusters (Hair et al., 2010). We proceed with a four-cluster solution because it implies less heterogeneity than the other cluster solution (Hair et al., 2010). The non-hierarchical cluster analysis results in cluster size of 22, 12, 13, 6 cases respectively. The difference in the variables means across four clusters are statistically significant. Table 8 presents the whole group clustering classifications.

Table 3. Means from non-hierarchical three cluster solution (N = 81)

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. *Obstacles*	1.7500	2.2083	*2.7308*	**1.3333**	3.435	0.025
Size of the clusters	22	12	13	6		

Source: Author

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 reputational risk to AI adoption. Therefore, in this study these two factors cannot be taken into investigated both technological readiness and environmental readiness.

Next, these four clusters showed different levels of AI awareness, attitudes, and obstacles.

Cluster 1 exhibits a moderate understanding of AI. Despite not having the highest level of AI knowledge, this group maintains a relatively positive attitude towards AI. They also encounter relatively few obstacles in their initiatives. This cluster is the largest having 22 companies.

Cluster 2 shows the lowest understanding level of AI. Surprisingly, this lack of understanding does not dampen their enthusiasm (4.1667). However, they face moderate obstacles in their AI efforts. Despite their positive outlook, the combination of low understanding and moderate obstacles might post challenges. This cluster consists of 12 companies.

Cluster 3 represents companies with a below-average understanding of AI. Their attitude towards AI is moderate, but they face the highest level of obstacles among the clusters (2.7308). This indicates that while they are not entirely pessimistic about AI, the significant challenges they encounter may hinder their progress. This cluster includes 13 companies, and reflects a fairly common scenario where moderate attitudes and higher obstacles coexist.

Cluster 4 has a relatively low understanding of AI, and also exhibits the lowest attitude towards AI. However, this group encounters the fewest obstacles (1.3333). This suggests that while they may not be very knowledgeable or enthusiastic about AI, they do not face significant barrier either. This is the smallest including 6 companies.

Overall, these clusters illustrate the diverse landscape of companies' AI experiences, with significant differences in their understanding, attitudes, and the challenges (internal data scarcity and less external financial support) they face. Our results suggest that firstly, clusters with higher understanding of AI might be more advanced in their technological adoption and innovation strategies. This is aligned with the finding of Schiave et al. (2024). The higher degree of AI literacy contributes to the overall acceptance of AI-based technologies.

Finally, three research hypotheses in our study have been tested and verified, the results are shown in the Table 9 below。

Table 4。 Research Hypotheses Validation Results

Hypothesis 1	Different groups of companies are characterized by different level of technical readiness and adoption of AI applications	Partial accepted
Hypothesis 2	Different groups of companies are characterized by different level of organizational readiness and adoption of AI applications.	Accepted
Hypothesis 3	Different groups of companies are characterized by different level of environmental readiness and adoption of AI applications and adoption of AI applications.	Partial accepted

Source：Author

The final cluster solution requires profile the clusters with additional and not used before variables. In this study demographic characteristics are used: (1) ownership, (2) area of country, (3) sector, (4) decision-making process, (5) size of company, (6) planning intensity, (7) innovation intensity. These variables are nonmetric, and then relationships are tested by a cross-tabulation and the chi-square values. The chi-square values of these variables are significant is only plan intensity - not adopting any AI applications now and in the next two years (Sig.=0.005), as shown in the Table 10.

Among three kinds of indicators of the usage intensity, there is one indicator called plan intensity. This indicates that the likelihood of adopting AI applications now and in the next two years significantly differs across the clusters. Some clusters are more inclined to delay AI adoption compared to other clusters.

Table 5. Chi-square test result, no plan no use

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	20.269[a]	9	.016
Likelihood Ratio	21.599	9	.010
Linear-by-Linear Association	5.042	1	.025
N of Valid Cases	53		

a. 12 cells (75.0%) have expected count less than 5. The minimum expected count is .23.

Source: author

Although we did not find any clues among these demographic variables such as: (1) ownership, (2) area of country, (3) sector, (4) decision-making process, (5) size of company, (7) innovation intensity, and their impact on AI adoption. We observed that planning intensity is vital to AI adoption. Clusters that are plan to adopt AI applications now or in the next two years may face potential competitive disadvantages as AI technologies continue to evolve and become more integral to various sectors.

2.5. Second Cluster Analysis

Given that *AI awareness* and *attitudes* and Obstacles 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 (use dummy, intensity of use, intensity of planning, and deeper understanding variables). Four cluster centres were finally 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 (Table 11).

Table 6. K-means cluster analysis

Final Cluster Centres				
	Cluster			
	1	2	3	4
In depth understanding	7,06	1,73	1,52	2,32
Usage Intensity	1,11	6,45	0,52	1,32
Plan Intensions	2,72	0,91	0,36	4,89
usage (no/yes)	0,56	1	0,33	0,74

Source: author

On the other hand, the ANOVA analysis results show the performance of the analysis of variance of different variables in each cluster. 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 12).

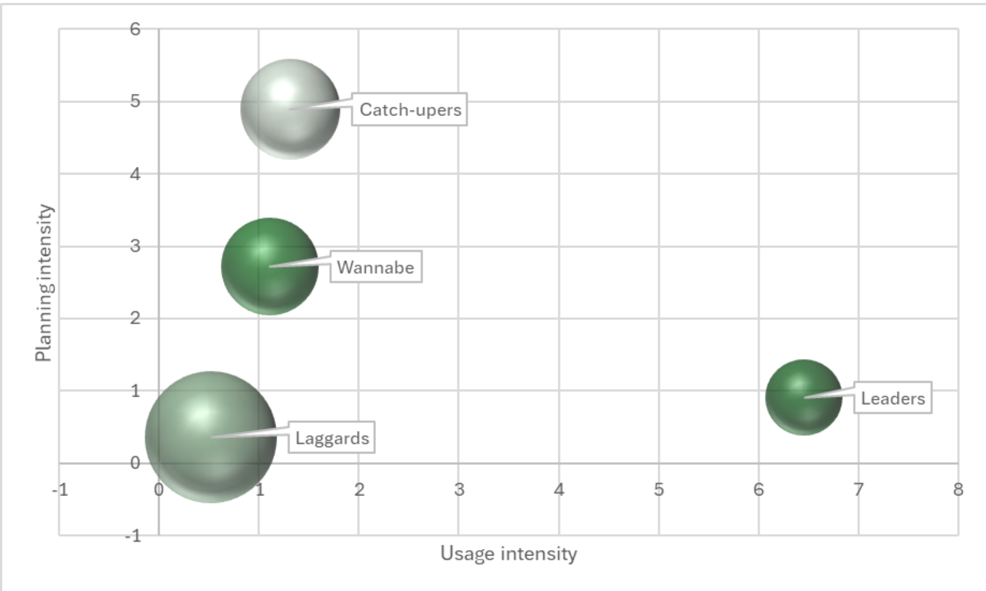
Table 7. Result of ANOVA analysis

ANOVA						
	Cluster		Error		F	Sig.
	Mean Square	df	Mean Square	df		
In depth understanding	131,805	3	2,643	77	49,879	0
Usage Intensity	101,255	3	1,284	77	78,871	0
Plan Intensity	90,002	3	1,714	77	52,522	0
usage (no/yes)	1,472	3	0,201	77	7,328	0

Source: Author

After analysing 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 (Figure 5):

Figure 5. Four categories of AI practice.



Source: Author

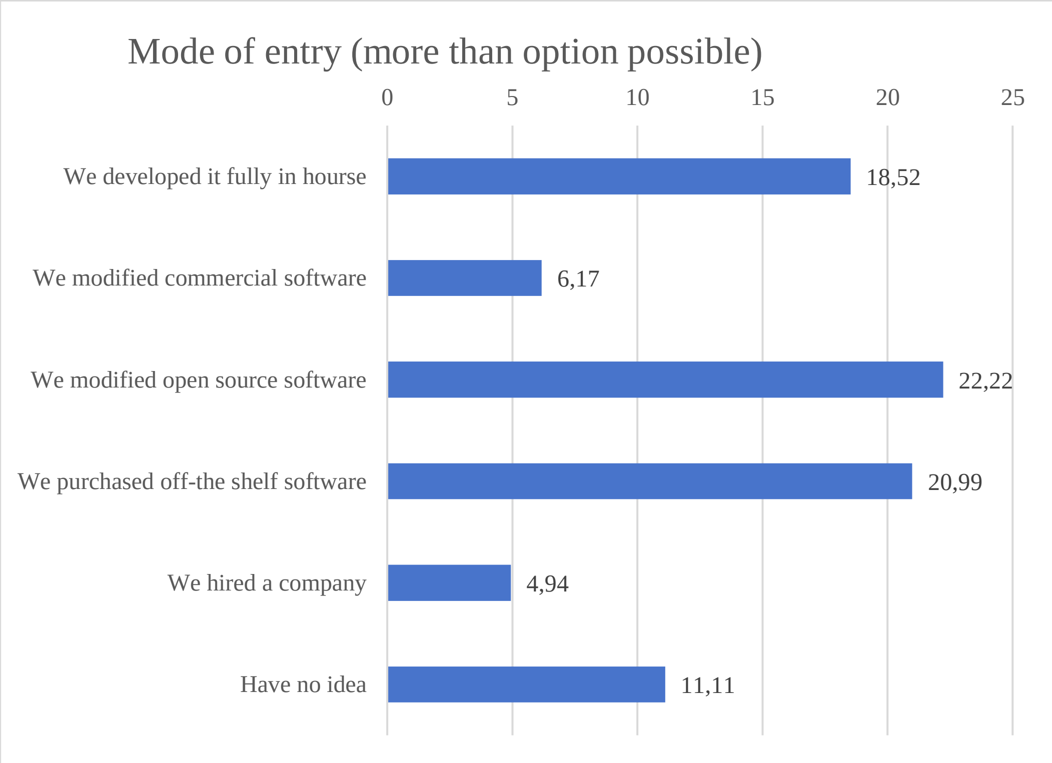
Cluster 1, with 22% of the cases comprise of companies which claim a very high level of understanding of many different aspects of AI (variable in-depth understanding) however with significantly lower usage intensity and even low AI experimentation history. The discrepancy between understanding and usage 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” probably responded to the questions about understanding socially acceptable and how they would like to see themselves.

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 6. Mode of entry (multiple options)



Source: author

The way the AI enters a company could be very different. Experimentation comes with off-the shelf products like GenAI (ChatGPT), Canva, anomaly detection for e-commerce shops, chat-integration (previously with services like Chatfuel) all the way to the custom solutions with machine learning integration in the decision-making software the firm could have.

There is a notable difference in the channels of entry of AI based on the clusters (Figure 6). For instance, the leading companies will develop their AI predominately internally, while the catch-uppers will modify open sources solution and the laggards will prefer to buy off-the-shelf products, mainly because they will lack internal competence. The cluster of the laggards have significantly lower organizational capacity (variable orgcapacity).

Specifically, organizations can tailor educational and support programs to increase AI understanding in clusters lagging in this area. This could involve workshops, training sessions, and collaboration with AI experts. Also, encourage clusters hesitant to adopt AI to engage in strategic planning sessions to understand the long-term benefits, and potential ROI of AI technologies. Furthermore, allocate resources efficiently by focusing on clusters that show readiness and potential for AI adoption to maximize impact.

Therefore, organizations can better strategize their AI implementation plans, leading to more informed decision-making and optimized resource allocation.

CONCLUSION

This dissertation aimed to uncover and analyse the factors that are related to AI readiness and adoption across different groups of companies in Bulgaria. The study focused on how different groups of companies are characterized by varying level of technical, organisational, and environmental readiness and their subsequent adoption of AI applications. In pursuit of this these objectives, the following tasks have been accomplished.

Literature Review. We conducted a comprehensive literature review on the topic of artificial intelligence (AI). Key tasks included: Firstly, we presented an overview of main definitions of AI, its components, and its applications across different industries. Secondly, we analysed the current state of AI in Bulgaria using the PEST analysis framework. Thirdly, we outlined the theoretical foundation for acceptance of new technologies and the factors related to readiness and/or adoption of AI. Finally, we developed a research model with hypotheses based on factors within the technological, organizational, and environmental framework to explore the adoption of AI in the context of Bulgarian firms.

We conducted an empirical study on factors related to the readiness and adoption of AI in the context of Bulgarian firms. For this reason, we designed an online survey and collected 223 responses, out of which 81 responses, which were used in the analysis, 50 of which full responses. Next, we performed factor analysis and two cluster analyses to verify the proposed hypotheses and model. The validation results are:

H1: Different groups of companies are characterized by different level of technical readiness and adoption of AI applications. --- Partially accepted

H2: Different groups of companies are characterized by different level of organizational readiness and adoption of AI applications. --- Accepted

H3: Different groups of companies are characterized by different level of environmental readiness and adoption of AI applications and adoption of AI applications. --- Partially accepted

MAIN CONTRIBUTIONS OF THE DISSERTATION

1. This study contributes to the enrichment of the literature on AI adoption within the Bulgarian environment. It operationalized new mechanism from the TOE framework by considering different groups of companies that are characterized by different level of technological, organisational, and environmental readiness and adoption of AI applications.

2. This study identifies three dimensions of AI readiness, related to AI adoption. In the technological dimension, the richness of internal data is important; in the organisational dimension the AI awareness and attitudes are important; and in the environmental dimension external funding is vital.

3. This study discovers the behaviour of Bulgarian companies in practical AI adoption, on the basis of in depth understanding and usage intensity. Subsequently, it defines four types of players regarding adopting AI technologies. They are leaders, laggards, catch-uppers, and wannabe.

4. Based on the clusters, this study demonstrates notable differences in the channels of entry of AI. The leading companies develop their AI predominately internally,

while the catch-uppers modify open sources solution and the laggards prefer to buy off-the-shelf products.

5. This study provides insights to businesses and policy-makers when making strategic decisions regarding resource allocation, governance structure, and policy development related to AI.

6. This study suggests also venues for further investigations such as: impact of firms' demographic characteristics on AI adoption; and AI promotion strategies tailor to different groups.

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1	Ma Lingling, Technological innovations in agricultural firms in Bulgaria: what is the role of EU Funds? Proceedings of the International Conference of Business Excellence, Publisher: Sciendo, 2024, pages:1647-1657, ISSN (online):2558-9652,	2024
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3	Ma Lingling, Artificial Intelligence Readiness and Adoption in SMEs, Journal of Economic Boundaries and Transformation, Issue 1, 2023	2023
4	Ma Lingling, Information and Communication Technologies, Innovation.BG: Innovation and Sustainable Growth, Publisher: ARC Fund, 2023, pages:58-62, ISBN:978-954-9456-36-3	2023