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AI adoption and Digital Transformation in Greek SMEs :
Readiness, barriers and the day after

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Patras, Greece, May 2026

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AI adoption and Digital Transformation in Greek SMEs :

Readiness, barriers and the day after

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Abstract

The dissertation examines the influence of technological factors in Artificial Intelligence (AI) adoption in Greek Small and Medium Enterprises (SMEs) through a quantitative exploratory survey. The survey was performed through an online questionnaire. The analysis suggested limited adoption of AI among Greek SMEs. Moreover, the results imply that digital maturity in terms of infrastructure is at an average level but utilization and data readiness appear to be lagging in comparison. The inferential analysis was based on the technological context of the Technology-Organization-Environment and Diffusion of Innovation (TOE-DOI) framework for technology adoption. The constructs tested were Infrastructure, Information Technology (IT) Knowledge, Data Readiness, Compatibility and Complexity and their influence was tested on AI adoption state and AI adoption intention. The Exploratory Factor Analysis (EFA) suggested that the first four factors exhibit high correlations and merge into two latent factors, the one possibly representing the existence of resources and the other the utilization of resources and AI readiness. Linear Regression Analysis with the initial model demonstrated strong influence from Data Readiness, Compatibility and Complexity on AI adoption state and from Data Readiness and Compatibility on AI adoption intention. A second model with empirical reasoning was used that aggregated the first four constructs into a Digital State and AI Readiness variable. The second model exhibited comparable explanatory power with the initial, while significantly simpler, suggesting a possible holistic treatment of Digital State and AI Readiness by Greek SMEs.

The dissertation makes an exploratory contribution to the analysis of the influence of the technological context on AI adoption state and AI adoption intention in Greek SMEs. It complements classical TOE-DOI items with Data Readiness and digital resource utilization items. Empirical evidence indicated that the utilization and data readiness matter strongly, while there is some indication that the technological factors may behave more holistically than purely orthogonal in this context.

Keywords

Artificial Intelligence adoption, Digital transformation, Greek SMEs, TOE-DOI framework, Digital maturity

Περίληψη

Η διατριβή εξετάζει την επιρροή των τεχνολογικών παραγόντων στην υιοθέτηση της Τεχνητής Νοημοσύνης (TN) από τις ελληνικές Μικρές και Μεσαίες Επιχειρήσεις (ΜΜΕ) μέσω μιας διερευνητικής ποσοτικής έρευνας. Η έρευνα πραγματοποιήθηκε μέσω ενός δικτυακού ερωτηματολογίου. Προέκυψε περιορισμένη υιοθέτηση της TN από τις ΜΜΕ. Επιπροσθέτως, τα αποτελέσματα υποδηλώνουν ότι η ψηφιακή ωριμότητα σε όρους υποδομής βρίσκεται σε μέτριο επίπεδο αλλά η χρήση ψηφιακών συστημάτων και η οργάνωση δεδομένων υστερούν συγκριτικά. Η συμπερασματική ανάλυση βασίστηκε στο τεχνολογικό πλαίσιο του μοντέλου TOE-DOI. Τα constructs που ελέγχθηκαν ήταν τα Infrastructure, IT Knowledge, Data Readiness, Compatibility και Complexity, ενώ οι εξαρτημένες μεταβλητές ήταν το AI adoption state και AI adoption intention. Η EFA υποδηλώνει ότι οι τέσσερις πρώτοι παράγοντες συμπύσσονται σε δύο, με τον πρώτο πιθανότατα να αντιστοιχεί στην ύπαρξη πόρων, και το δεύτερο στη χρήση πόρων και την ετοιμότητα για TN. Η γραμμική παλινδρόμηση με το μοντέλο που βασίζεται στους αρχικούς παράγοντες δείχνει ότι στατιστικά σημαντική επιρροή έχουν στο AI adoption state, τα Data Readiness, Compatibility, Complexity και στο AI adoption intention το Data Readiness και το Compatibility. Ένα δεύτερο εμπειρικό μοντέλο το οποίο συνενώνει τους τέσσερις πρώτους παράγοντες στο Digital State and AI Readiness δοκιμάστηκε και επέδειξε συγκρίσιμη επεξηγηματική ικανότητα παρότι είναι απλούστερο μοντέλο.

Η διατριβή κάνει μια διερευνητική συνεισφορά στην ανάλυση της επίδρασης του τεχνολογικού πλαισίου στην υιοθέτηση TN από τις ελληνικές ΜΜΕ. Συμπληρώνει τα κλασικά TOE-DOI ερωτήματα με ερωτήματα οργάνωσης δεδομένων και χρήσης ψηφιακών συστημάτων. Εμπειρικά συμπεράσματα υποστηρίζουν ότι η οργάνωση δεδομένων και ψηφιακών συστημάτων έχει ισχυρή επίδραση στην υιοθέτηση, ενώ υπάρχουν ενδείξεις ότι οι τεχνολογικοί παράγοντες γίνονται αντιληπτοί από τις ΜΜΕ ως ένας πιο ολοκληρωμένος παράγοντας και λιγότερο ως ορθογώνιες διαστάσεις.

Λέξεις – Κλειδιά

Υιοθέτηση Τεχνητής Νοημοσύνης, Ψηφιακός μετασχηματισμός, Ελληνικές ΜΜΕ, TOE-DOI μοντέλο, Ψηφιακή ωριμότητα

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List of Abbreviations & Acronyms

AI	Artificial Intelligence
AII	Artificial Intelligence adoption intention
AIS	Artificial Intelligence adoption state
ANOVA	Analysis of Variance
ASEAN	Association of Southeast Asian Nations
BCG	Boston Consulting Group
CV	Computer Vision
DL	Deep Learning
DOI	Diffusion of Innovation
EFA	Exploratory Factor Analysis
EU	European Union
EUR	Euro
HR	Human Resources
IBM	International Business Machines Corporation
ICT	Information and Communication Technology
IEEE	Institute of Electrical and Electronics Engineers
INSEAD	Institut Europeen d'Administration des Affairs
IS	Information Systems
IT	Information Technology
KMO	Kaiser-Meyer-Olkin measure
LLM/LLMs	Large Language Model(s)
MBA	Master in Business Administration
MIT	Masachusetts Institute of Technology
ML	Machine Learning
NBG	National Bank of Greece
NLP	Natural Language Processing
OECD	Organisation for Economic Co-operation and Development
PAF	Principal Axis Factoring
PCA	Principal Component Analysis
PEOU	Perceived Ease of Use
PESTLE	Political, Economic, Social, Technological, Legal and Environmental

POS	Point of Sale
PU	Perceived Usefulness
ROI	Return on Investment
RPA	Robotic Process Automation
SEPE	Federation of Hellenic ICT Enterprises
SME/SMEs	Small and Medium Enterprise(s)
SPSS	Statistical Package for the Social Sciences
TAM	Technology Acceptance Model
TAM2/TAM3	Technology Acceptance Model 2 / 3
TOE	Technology-Organization-Environment
UTAUT	Unified Theory of Acceptance and Use of Technology
UTAUT2	Unified Theory of Acceptance and Use of Technology 2
VIF	Variance Inflation Factor

1. Introduction

1.1 Background and Motivation

Artificial Intelligence (AI) is currently a concept surrounded by considerable hype and expectations (Chui et al., 2023; Gartner, 2023). Parts of the business community predict that its applications are going to be a transformational factor for businesses that will lead to large profit increases, while businesses lagging in adoption are going to lose their competitive advantage. However, such predictions are often based on strong assumptions and should be interpreted with caution. Beyond the hype, AI is a technology that has the potential to offer advantages, among which cost reduction, improved marketing performance and increased resource efficiency having applications among most of the business functions. Moreover, it should be able to reduce the bureaucratic burden of businesses and improve employee performance.

Generative AI (GenAI) presents some new possibilities that could potentially offer small businesses services that they had limited or no access to before. Some capabilities that require either specialized departments or expensive external consulting services were hardly available to smaller businesses. Especially Small and Medium Businesses (SMEs), and specifically the smaller among them, can now access these services through GenAI even if only at an introductory level. GenAI could act as a marketing consultant, could help create business plans, or assess the strengths and weaknesses of a business and give advice on the potential steps to improvement. However, the members of the business should always assess the suggestions since AI can still be mistaken.

1.2 Research Question and Research Gap

Based on these ideas, this dissertation examines the adoption of Artificial intelligence in SMEs which are the backbone of the Greek economy. Furthermore, while they are candidates for value-adding AI adoption, they face significant barriers in adopting and integrating AI into their operations. For that reason, research on AI adoption among Greek SMEs and the factors that influence it is useful and academically interesting. Moreover, a significant research gap appears to exist in the relevant research because primary quantitative inferential research regarding AI adoption in Greek SMEs remains limited. Therefore, the research idea of this thesis is to examine the relationship between the current

state of digital transformation of a business and its AI adoption. This research investigates how technological readiness factors and digital state of a business influence AI adoption state and AI adoption intention in Greek SMEs. The results are expected to provide useful insights on how to improve AI readiness among Greek SMEs.

The dissertation aims to assess AI adoption on Greek SMEs and examine the state of technological readiness factors. Importantly this research tries to investigate the state of Data Readiness and the influence that it may exert along the other technological factors to AI adoption. Moreover, this research aims to assess whether the technological factors behave independently or if they correlate for Greek SMEs. Additionally, the research aims to include the utilization of digital resources in the analysis, to assess whether it groups with the existence of resources or has a distinct behavior.

The importance of AI is also supported by global adoption trends. Literature-based findings, which are presented in detail in section 2, indicate a rapid increase in use of AI in businesses in recent years, most importantly between 2023-2025. The trend is consistent both in Greece and across the world. The statistics suggest that AI is mainly in pilot or experimenting phase in most businesses while a fully integrated implementation is much less frequent and limited to specific functions. Available studies indicate that Greece lags compared to US and worldwide adoption but is not severely lagging the EU average. Among the businesses, it is the smaller ones that appear to lag in AI use and adoption.

1.3 Conceptual Foundations and Definitions

To better establish the research question, some conceptual foundation is required. First, a definition of AI is provided. Organisation for Economic Co-operation and Development (2024) based on Russell and Norvig (2009) has defined AI systems as “*a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments. Different AI systems vary in their levels of autonomy and adaptiveness after deployment*”. However, for the purposes of this dissertation, Gartner’s (2025) definition, which focuses on the applied aspects of AI in business, is more relevant. Gartner (2025) defines AI as “*applying advanced analysis and logic-based techniques, including machine learning (ML), to interpret events, support and automate decisions, and take actions*”.

Digital Transformation, which was examined in relation to AI, is defined by Vial (2019) who builds on Bharadwaj et al. (2013) as *“a process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies”*. These changes aim according to Kargas et al. (2023) to *“expand existing business models, to transform organizational structures, to alternate how resources are used and to reevaluate relationships with stakeholders”*.

While Digital Transformation refers to the process of adopting digital systems in business functions Digital Maturity discusses the state the business has progressed to (Schumacher, 2016; Gökalp & Martinez, 2021). Kane et al. (2017) defined Digital Maturity as being about *“adapting the organization to compete effectively in an increasingly digital environment”*. This definition encompasses beyond the state the ability to adapt which could point towards the suggested influence of technological readiness on AI.

Furthermore, since the dissertation is discussing SMEs, they should also be defined. According to European Commission Recommendation 2003/361/EC, SMEs are *“enterprises that employ fewer than 250 persons and have an annual turnover not exceeding 50 million EUR and/or annual balance sheet total not exceeding 43 million EUR”* (European Commission, 2020). Moreover, SMEs are divided in sub-categories according to Table 1.

Table 1. SME classification (European Commission, 2020)

Enterprise Category	Staff Headcount (AWU)	Annual Turnover	Annual Balance Sheet Total
Medium-sized	< 250	≤ EUR 50 million	≤ EUR 43 million
Small	< 50	≤ EUR 10 million	≤ EUR 10 million
Micro	< 10	≤ EUR 2 million	≤ EUR 2 million

SMEs constitute 99.9% of all Greek enterprises, they employ 84.7% of all employees and present 62.8% of the added value of the Greek economy (European Commission, 2025).

AI encompasses a wide range of technologies which have various potential applications among the businesses' functions. Some of them are:

1. **Machine Learning (ML):** Machine Learning is a branch of AI which according to Jordan & Mitchell (2015) “addresses the question of how to build computers that improve automatically through experience”. More concretely, it means that the computer systems use “algorithms to identify and learn patterns in data, apply that learning to improve themselves to make better and better decisions” (Le Dinh et al., 2025). In essence, the ML algorithms use data to find statistical correlations among them and perform either classification or estimation which helps the user predict the future, see patterns which can help in business optimization and finally make the decisions that lead to advantage.
2. **Expert Systems and Knowledge-Based Systems:** This is one of the older branches of AI where preprogrammed rules are used to make automatic decisions. Since it is based on preprogrammed knowledge it requires less data than other AI forms, and is thus easier to adopt, but can fail easier for unexpected inputs (Buchanan & Smith, 1988; Le Dinh et al., 2025). To avoid this shortcoming, recently it has been combined with other techniques into hybrid solutions (Huin et al., 2003).
3. **Generative AI:** This branch of AI is the newest and among the most popular. Generative AI (GenAI) systems are capable of creating original content (text, pictures, sound, video) after being trained by very large datasets. Contrary to many other types the same system can tackle various completely different problems. Another advantage of GenAI, is the ability to use a very large amount of data as input to define its task, like directions, or knowledge needed for the specific task (for instance the documents of the business so that the GenAI can find specific entries or answer specific questions). GenAI though has also some drawbacks. It is resource heavy and difficult to implement locally, while it has also the tendency to sometimes create fictitious results with no relation to the problem’s data (Rajaram & Tinguely, 2024; Le Dinh et al., 2025; Implement Consulting Group, 2024; Federation of Hellenic ICT Enterprises (SEPE) & Deloitte Business Solutions S.A., 2023).

Other types of AI are: **Deep Learning (DL)**, Natural Language Processing (NLP), **Computer Vision (CV)**, **Robotic Process Automation (RPA)** (Buchanan & Smith, 1988; LeCun, Bengio, & Hinton, 2015; Van der Aalst, Bichler, & Heinzl, 2018; Szeliski, 2022; Tzampazaki et al., 2024; Kanellopoulou et al., 2025; Le Dinh et al., 2025). This characterization exhibits overlaps but is sufficient for the needs of the present thesis.

These types of AI have applications in multiple functions of the businesses. In Sales and Marketing, AI can be used for sales forecasting, whereas chatbots can be used for customer

service and GenAI can be used for digital content creation (Schönberger, 2023; Rajaram & Tinguely, 2024; Le Dinh et al., 2025). These integrations of applications can reduce costs and achieve better marketing performance, but they can be combined with Logistics, where AI can, for example, help with Inventory management (Kanellopoulou et al., 2025) or Delivery route optimization (Iyelolu et al., 2024). Such integrations could potentially result in cost cuts across the spectrum. In Operations, AI can predict Machinery failures or do quality assurance (Oldemeyer et al., 2025), thus achieving less production downtime or avoiding selling defective products. Moreover, it can aid in Finance and Accounting or Human Resources (Yi et al., 2023; Schwaeye et al., 2025), Risk Management and Cybersecurity (Schwaeye et al., 2025) or general Information Systems (Buxmann et al., 2021), where it can help the business avoid accounting pitfalls or digital security risks, further securing the smooth business operation. An important function for some businesses is Research and Development, where it can help with decision making, assess success possibilities and facilitate innovation (Le Dinh et al., 2025; Iyelolu et al., 2024). A final function where AI can have significant contribution, also encompassing other functions, is Business Intelligence and Analytics. By its nature of data processing, AI can help create recommendations and identify patterns that guide business decisions (Le Dinh et al., 2025; Schönberger, 2023). A remark related to the findings of this dissertation is that most of these applications require the existence of data, usually well organized to provide successful results.

1.4 Theoretical Framing

Digital transformation is a broad term that may include the adoption of different technologies, one of which could be AI (Vial, 2019). In a narrower context, it describes the introduction and use of digital technologies to support and digitalize the business operations and organizational functions. In that context, digital transformation and its resulting digital maturity/state may be described through tangible and intangible digital resources like IT infrastructure, related knowledge and data resources. Moreover, it may refer to the digitalization of business functions and the storage and utilization of data. The question is whether this digital state acts as AI readiness and influences AI adoption.

To examine the research question, various technology adoption frameworks were reviewed. Technology acceptance model (TAM) and its derivative frameworks focus more on the

personal factors facilitating adoption like Perceived Usefulness or Perceived Ease of Use. The TOE framework focuses more on the organizational factors across technological, organizational and environmental contexts, while DOI (Diffusion of innovations) focuses more on the technology characteristics and how they influence adoption. The research question matched the characteristics of TOE and especially of the combined models of TOE with DOI (TOE-DOI). Since the question assesses Digital Transformation and Maturity and its relation to AI adoption the dissertation only focuses on the technological context. Specifically, not only the influence of resources but also of the utilization of resources are examined in this research. Limited research appears to exist using the technological context of TOE-DOI to assess the influence of digital transformation and digital state or maturity on AI adoption in Greek SMEs. Furthermore, Data Readiness and digital systems' utilization inclusion in TOE-DOI research has also been limited. Therefore, this dissertation also contributes by exploratorily incorporating such items into the TOE-DOI framework.

1.5 Dissertation Structure

The dissertation is organized as follows:

- **Chapter 1 - Introduction:** The research question is introduced, necessary definitions are developed and the focus of the research is explained.
- **Chapter 2 - Literature Review:** This chapter contains a discussion of AI barriers as they appear in literature. It continues with descriptive statistics about AI adoption across the world and in Greece. Afterwards, it proceeds with the literature discussion of theoretical frameworks, emphasizing TOE-DOI, a critique on the model and the Construct Selection. The chapter finishes with the Hypotheses formulation.
- **Chapter 3 - Methodology:** In Methodology the survey design is justified and the analysis choices are presented.
- **Chapter 4 - Results:** In Results chapter the analysis of the survey's results is presented, starting with Descriptive statistics and continuing to an Exploratory Factor Analysis and Regression models to assess whether the Research Hypotheses are supported.

- **Chapter 5 - Discussion:** In the Discussion chapter the results are further analyzed, while the chapter ends with proposals to improve both Digital State and AI adoption for Greek SMEs
- **Chapter 6 – Conclusion:** Conclusion chapter summarizes the dissertation's results, states the limitations and future research directions are suggested based on these conclusions.

2. Literature review

2.1 AI adoption in SMEs in the world and Greece

Data and Literature on actual adoption of AI in businesses are primarily provided by organizations with access to large business samples, such as state institutions or large consulting firms. This section first reviews worldwide and US statistics, which then serve as a benchmark for comparison with evidence from Greece.

In Singla et al. (2025) research covering all business sizes and a worldwide sample almost 90% of the respondents report that they regularly use GenAI. However, 62% remain in pilot or experimental use. Only half of the respondents report using AI in more than two business functions. Among the smaller businesses (part of which are SMEs) only 30% are in scaling or fully scaled AI phases, with 39% being in pilot or experimental phases. This study supports the view that company size influences AI adoption.

OECD, BCG and INSEAD (2025), in a survey in G7 countries and Brazil focusing on manufacturing and ICT sectors, indicated that the percentage of medium companies that adopt AI was half that of large companies. Similarly, the percentage of small companies adopting AI was half that of medium companies. Using 2023 data, they reported single-digit adoption rates across the sample. The adoption ratio between company sizes seems consistent with other research.

U.S. Chamber of Commerce (2025) reports findings on AI and technology adoption in small US businesses (which roughly correspond to EU SMEs) using 2025 data. Businesses self-reported GenAI use at 58%, up from 40% in 2024 and 23% in 2023. The vast majority (96%) of them reported intentions to adopt emerging technologies including AI. The majority (63%) reported that they rely on tools by other companies, and 77% of them felt unprepared to comply with AI regulations. Finally, the highest AI adoption was among Technology, Financial Services and Entertainment/Media sectors while the lowest adoption was reported by Retail and Manufacturing. However, Sánchez et al. (2025), according to their global literature synthesis, suggest that more than 90% of SMEs have no AI applications in place.

Despite inconsistencies due to differences in sample structure, survey years and emphasis on GenAI or general AI, some patterns appear consistent. Smaller businesses exhibit significantly lower adoption rates compared to larger ones, approximately halving between

company size categories. Another important finding, especially among more recent datasets, is the broad GenAI adoption, although adoption mostly remains at an experimental or pilot phases.

The same trend also appears within the European Union. In EU, according to Eurostat (2025), using 2024 data, businesses use at least one AI technology at 13.48%. The distribution for small, medium and large enterprises is 11.23%, 20.97% and 41.17% respectively, which is consistent with the adoption ratios between business size categories reported worldwide. Denmark performed best with a 28% adoption rate and Romania the worst at 3% with Greece slightly below the 13% EU average at 10% (Figure 1). In terms of adoption distribution per sector, EU results follow the worldwide trend, and in terms of business function, SMEs most frequently use AI in marketing and sales (Figure 2).

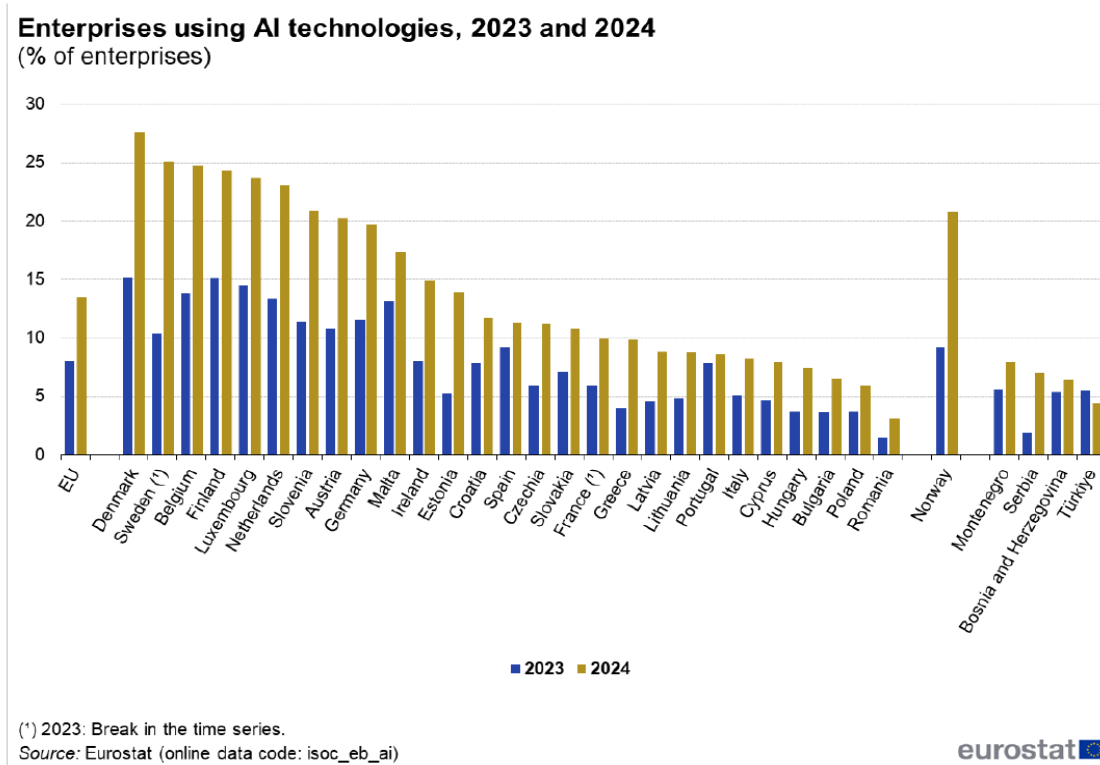
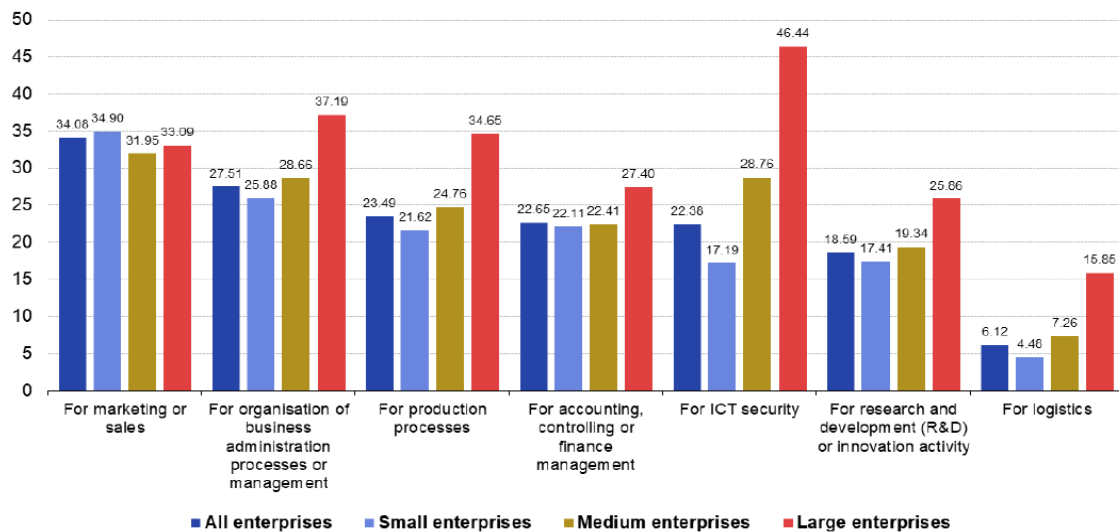


Figure 1. Use of AI per Country (Eurostat (2025), Figure 2).

Enterprises using AI technologies by type of purpose and size class, EU, 2024

(% of enterprises using at least one AI technology)



Source: Eurostat (online data code: isoc_eb_ai)

eurostat

Figure 2. AI use per business function (Eurostat (2025), Figure 5).

Additional EU data from OECD, BCG and INSEAD (2025), using 2023 data, corroborate the lower AI adoption in the EU, with an average adoption rate of 8% compared to 13% for Brazil based on 2021 data. Schönberger (2023) presents data about German enterprises, which support the sectoral distributions presented in other research with ICT sector adopting at a higher rate while manufacturing exhibits the lowest adoption rates. These trends remained consistent between 2022 and 2023.

According to Implement Consulting Group (2024), 35% of Greek businesses reported that their employees regularly use GenAI. Furthermore, this report also supports the existence of significant adoption differences between business size categories, with large businesses exhibiting 14% AI adoption rate compared to SMEs 4% using 2023 data. Furthermore, 31% of Greek SMEs report “some use” of AI according to National Bank of Greece (2025). The adoption rates for Medium, Small and Micro enterprises are 40%, 30% and 23% respectively.

Kanellopoulou et al. (2025), with data from 2020 to 2022, report that among the businesses that expressed interest in exploring AI 26.4% were small and 17.6% were micro enterprises. A Federation of Hellenic ICT Enterprises (SEPE) & Deloitte Business Solutions S.A. (2023)

survey highlights that most Greek businesses believe that GenAI can help improve productivity (83%) and business growth (82%). However, only 9% have a strategy for GenAI integration, while 31% of the businesses outside the ICT sector are either experimenting or actively using GenAI.

In conclusion, while Greek SMEs report lower AI adoption rates than the EU and global benchmarks, awareness and willingness to initiate AI integration are present. The literature indicates that GenAI reduces the burden of adoption and enables businesses to begin experimenting with AI at a low cost before scaling implementation. The most consistent result is that smaller businesses exhibit lower AI use rates compared to larger businesses, while ICT sector is the sector exhibiting the highest adoption rates. The business function most frequently reported as integrating AI first is Marketing and Sales. Finally, the variation in adoption rates among the literature can be attributed to different survey years, as well as whether studies focus specifically on GenAI or on AI adoption more broadly. GenAI usage, even at experimental or limited levels, is reported by a significantly larger percentage of businesses compared to other forms of AI adoption.

2.2 AI adoption barriers

AI adoption, similar to the adoption of other technologies in businesses, faces various barriers and challenges. These barriers relate to the nature of the technology itself, the pre-existing technological capabilities, the organizational capabilities of the business, as well as the environment in which the business operates.

Sánchez, Calderón, and Herrera (2025) state that the first group of barriers relate to the technological capabilities and readiness of the business. Compatibility of the processes and infrastructure is a significant barrier. The inability to integrate AI solutions into existing systems leads to reimplementing them, which requires time and has cost. Moreover, one more barrier is complexity, which pertains to how difficult the integration and use are perceived to be. If the business perceives the process as very difficult it is probable to avoid adoption. The third barrier is competence which combines material and immaterial resources. The material resources consist of the existing infrastructure like computers, servers and network connectivity. The immaterial resources relate to the knowledge and capabilities regarding the technology and general IT systems. This may include knowledge

but also experience in implementing, updating and configuring systems. Important among the resources is data readiness, which consists of data quality, availability and security (Sánchez et al., 2025). Oldemeyer et al. (2025) argue that most publications consider knowledge as the most significant barrier, but several others consider cost, acceptance or data as crucial factors. These factors roughly correspond to factors in Sánchez et al. (2025) (knowledge → competence, acceptance → complexity, data → competence). Among the previously named factors only cost is categorized as an organizational factor. Oldemeyer et al. (2025) also combine cost with the inability to hire external AI consultants, thus transforming the barrier into IT knowledge related barrier and thus a technological barrier. Moreover, they emphasize that digital maturity is lower in SMEs compared to larger enterprises.

The second category of barriers according to Sánchez et al. (2025) relates to the organizational aspect of the business. Four major barriers are identified: leadership, financial resources, human-resource competence, cultural readiness and change management. Leadership relates to whether the managers understand the benefits, secure resources, steer the company's culture and align the business strategy with AI adoption. Financial resources are an obvious barrier considering every technology adoption has cost. Human resource competence pertains to knowledge and capabilities at an organizational rather than technological level, which are necessary for the successful integration of AI in the business. Cultural readiness and change management relate to how the business manages resistance to change and how it communicates the benefits to employees to build acceptance. Oldemeyer et al. (2025) identify difficulties in assessing ROI as a barrier especially for SMEs.

The third category consists of environmental barriers. These appear in most PESTLE analyses examining AI barriers or critical factors. While PESTLE models external macro-environment, some aspects reported in Oldemeyer et al. (2025) belong to the technology and organizational aspects previously described. This is expected since technology is considered an external factor in PESTLE. Factors reported are lack of guidance or funding, the availability of AI solutions (which is a mix of technological and environmental factors) and lack of standardization which similarly combines technological and environmental factors. Regulatory compliance and data privacy are also mentioned. Rasdi & Baki (2025) have also identified regulatory compliance and lack of established policy as well as lack of

government infrastructure and funding support from institutions as problems. Sánchez et al. (2025) emphasize similar barriers such as regulatory uncertainty, restrictive legislation and lack of government support plans, including guidance and funding.

Many of these barriers can also be viewed as enabling factors when phrased in positive form. Among the technological, organizational and environmental factors, the technological factors and the cost-related organizational ones appear to be the most frequently reported.

2.3 Technology adoption frameworks

2.3.1 Introduction

Technology adoption frameworks model the relation between the adoption state of a specific technology and the factors that influence it. These factors are operationalized as latent constructs in inferential research.

Among the older frameworks is the Technology Acceptance Model (TAM) (Davis, 1989). It models the individual's acceptance of an information technology and willingness to use it. The model uses two constructs, the Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) and identifies PU as the dominant contributor, with PEOU having an indirect influence through PU.

Venkatesh & Davis (2000) revised TAM with TAM2, where they searched for determinants of PU. They found Subjective Norm, Image, Job Relevance, Output Quality and Result Demonstrability as major determinants. The model improved the explanatory power of TAM.

Later, Venkatesh et al. (2003) presented a unified model with higher explanatory power. The new model is called Unified Theory of Acceptance and Use of Technology (UTAUT) and models factors influencing both intention and actual usage. Factors identified in the model are Performance Expectancy, Effort Expectancy, Social Influence and Facilitating Conditions. Also, Gender, Age, Experience and Voluntariness of use were identified as indirectly moderating the expression of the main constructs.

TAM3 is another extension of the TAM model that brings together the determinants of PU from TAM2 with determinants for PEOU (Venkatesh & Bala, 2008). The additional determinants of PEOU are: Computer Self-Efficacy, Perception of External Control,

Computer Anxiety, Computer Playfulness, Perceived Enjoyment and Objective Usability. It was developed to guide managers on how acceptance could be increased.

The last individual targeted framework that was examined is UTAUT2 (Venkatesh et al., 2012) which is an expansion of UTAUT and is more consumer-oriented. Thus, it is less useful for SMEs.

Moving on from individual-focused frameworks, another important framework models the characteristics of the innovation itself and how it diffuses into society. This framework is Diffusion of Innovations (Rogers, 2003). It examines the phases of technology adoption, and how different user groups approach the adoption. The user groups it introduces are Innovators, Early Adopters, Early Majority, Late Majority and Laggards. While this framework is not used by itself in this dissertation, it is often integrated into other frameworks to expand their explanatory power (Sánchez et al., 2025).

While TAM and its derivatives focus on the individual and DOI focuses on the characteristics of the technology itself, TOE framework focuses on the organization. Factors relating to existing infrastructure or organizational structures can be modeled through TOE. The framework was first described by Tornatzky & Fleischer (1990). It is a conceptually broad framework which recognizes three categories of determinants for technological adoption. These are the technological, organizational and environmental contexts. TOE is consistent with DOI and can be integrated with it (Oliveira & Martins, 2011).

The technological context models what technological infrastructure the business already possesses but also which technologies are available for adoption even though not currently adopted. (Baker, 2012; Oliveira & Martins, 2011). This availability defines the limits of adoption and innovation. The innovations may be incremental or discontinuous, which relates to their impact on the business and if they completely change the way the business is working (discontinuous). Another characteristic of technologies and innovations according to Baker (2012) is if they are competence-enhancing or competence-destroying. A competence-enhancing technology integrates with the current knowledge and extends it, whereas a competence-destroying technology makes the previous knowledge obsolete and unnecessary. The technological knowledge within the business can also be considered part of the infrastructure (Baker, 2012).

The second context is the organizational context. This context is related to the organization of the business and encompasses dimensions such as the size and slack, formal and informal communication structures, vertical or horizontal organization, tight or relaxed control, financial and human resources and innovation culture. (Baker, 2012; Oliveira & Martins, 2011). Each of these organizational contributions has been demonstrated to have some connection with the ease of technology adoption and innovation. The management leadership, communication and support are also significant since managers may adopt a leadership friendly to innovation and promote this openness to innovation or they may hinder it.

Finally, the environmental context relates to the characteristics of the environment the business operates within. Among these are the industry structure as well as the competitive forces within the industry. Rapid adoption by competitors acts as a strong influence. Another industrial factor is the maturity of the industry or position within the industry life cycle. Growing sectors tend to adopt innovation while mature or declining ones may exhibit either behavior depending on their perception of the benefits of innovation. The presence or absence of technology providers is also critical (Baker, 2012). Furthermore, the regulatory environment is an important factor which can impede or boost innovation. For instance, overregulation may impede innovation, in the case of information technology adoption or it may force adoption of the innovation, such as in the case of low-emissions requirements (Baker, 2012).

2.3.2 TOE framework analysis

Baker (2012) argues that applications of the TOE framework have used different factors or measures for different technologies and contexts. Moreover, the TOE framework functions as a synthesis framework and does not prescribe a fixed set of constructs, allowing researchers to focus on different aspects depending on the technology and the context studied.

The TOE framework has recently been used to study AI adoption in SMEs, in both literature review papers (Sánchez et al., 2025; Schwaewe et al., 2025) as well as empirical studies (Almashawreh et al., 2024; Badghish & Soomro, 2024). Such studies emphasize the factors

that are especially important for successful AI adoption. The following section analyzes the factors most frequently cited as influencing adoption.

Technological

The technological context includes Compatibility, Complexity and Competence (Sánchez et al., 2025). Competence is an aggregate term for technological capabilities and consists of Infrastructure, IT Knowledge and Data Readiness.

The first core TOE construct examined here is Infrastructure (Lin and Lin, 2008; Awa and Ojiabo, 2016; Almashawreh et al., 2024). Infrastructure lies within the technological context and refers to the availability and quality of IT systems, in terms of hardware, connectivity and software applications. For AI systems, infrastructure allows for data collection and storage, supports pre-processing, facilitates system integration and provides resources for AI system execution, thus enabling adoption.

IT Knowledge has been consistently identified as critical to the adoption of technologies within the technological context of the TOE framework (Lin and Lin, 2008; Awa and Ojiabo, 2016; Almashawreh et al., 2024). IT knowledge is the capability to use, adapt and upgrade information systems. Its importance, beyond basic use, lies in facilitating the integration of the new technology into the existing systems which helps the organization realize business value, thus supporting adoption. Apart from the utilization aspect, IT knowledge can reduce the perceived complexity of AI, facilitating adoption.

Data readiness, which refers to structure, regularity of sampling, volume and coverage of business-related information, is particularly critical in data-driven technologies such as AI. Even though Sánchez et al. (2025) recognize it as a critical subdimension within the competence factor which also encompasses infrastructure and IT readiness, data readiness has not always been modeled as a construct in TOE or TOE-DOI literature. Nonetheless, data has been consistently identified in literature as an enabler of AI adoption (Bérubé et al., 2021; Grünbichler, 2023; Zavodna et al., 2024; Sánchez et al., 2025). Specifically, most AI techniques require either regular and structured data to function or very large data volumes or both. Therefore, data readiness is expected to significantly influence AI adoption.

Compatibility refers to the degree to which the business systems and processes are aligned with the technology to be adopted (Lin & Ho, 2011; Awa & Ojiabo, 2016; Badghish & Soomro, 2024; Sánchez et al., 2025; Schwaeke et al., 2025). It originates from DOI theory

within the TOE-DOI frameworks and is typically measured as a perceptual construct. Badghish & Soomro (2024) define it also as an alignment with values and needs of the business. In summary, compatibility addresses whether physical systems, procedures, organizational aspects and values are aligned with the technology. Compared to Infrastructure the distinction can be understood as follows: Infrastructure measures the existence of systems, while compatibility measures whether these systems are perceived as able to integrate or interoperate with the technology smoothly. Similarly, while values and organizational aspects fall in the organizational context of the TOE model, compatibility assesses the match of these to the technology and is therefore commonly classified within the technology context.

Complexity refers to the degree to which adoption of the technology is difficult and requires much effort and resources (Sánchez et al., 2025; Badghish & Soomro, 2024). It is also commonly measured as a perception-based construct. Compared to competence and compatibility, complexity refers more to the technology itself than the state of the business relevant to the technology. In essence, while competence and compatibility refer primarily to current organizational conditions, complexity captures the requirements imposed by the technology.

Organizational

Sánchez et al. (2025) define that the sub-constructs that build the organizational context are Leadership, Financial Resources, Human Resource Competence and Culture readiness and change management. This context is the most diverse among the literature, making a one-to-one correspondence between the constructs that appear in different papers more difficult.

Leadership has to do with the degree that managers of the business believe in the benefits of the technology adoption and take steps to support and materialize it (Sánchez et al., 2025). It also relates to managers having relevant knowledge and guiding the company in a systematic way (Almashawreh et al., 2024; Badghish & Soomro, 2024).

The second sub-construct in the organizational context is Financial Resources (Sánchez et al., 2025). The construct relates to the availability of financial resources relative to adoption costs. Schwaeke et al. (2025) and Badghish & Soomro (2024) combine financial and human resources into broader resource-related constructs, but each publication categorizes these constructs differently within the TOE framework.

Human Resource competence refers to the general capabilities and skills of employees, including organizational skills (Sánchez et al., 2025). Schwaeye et al. (2025) use a Knowledge sub-construct which also includes technological knowledge. Training, which is a sub-construct used by Almashawreh et al. (2024), can also be included here. These constructs relate to training as well as HR managers' ability to effectively respond to changing requirements created by AI adoption.

Culture readiness and change management are a sub-construct which relates to constructive learning environments, open communication, committed leadership (though this overlaps with leadership) and inspiring trust (Sánchez et al., 2025). Schwaeye et al. (2025) include leadership in the Culture construct but also education. The existence of a Rewards system is a sub-construct that Almashawreh et al. (2024) examine, and which could be grouped in Culture. Badghish & Soomro (2024) define the Sustainable human resource management in which they study the work-life balance, inclusivity and to what degree the workforce is helped to integrate the new needs. These constructs relate to employee satisfaction and creating conditions that facilitate employee acceptance of the technology.

The last sub-construct in the context is ability to assess ROI (Sánchez et al., 2025). Badghish & Soomro (2024) use the sub-construct Relative Advantage which is the degree to which the technology offers higher performance and higher financial returns than other technologies, but they categorize it within the technological context. These constructs are especially difficult to assess in SMEs, which complicates their practical assessment.

Environmental

Sánchez et al. (2025) define the sub-constructs competitive intensity, government policies and regulations, and broader economic conditions.

Competitive intensity refers to the competitive conditions in the market and whether competition influences the business towards adoption (Sánchez et al., 2025; Schwaeye et al., 2025). Badghish & Soomro (2024) also include Market Demands within the context. Government Policies and Regulations relate to the influence of facilitating policies and regulations (Badghish & Soomro, 2024) as well as to policies that could hinder adoption like data protection or privacy rules. Finally, Schwaeye et al. (2025) identify the entire business ecosystem as a factor whose development may facilitate technology adoption at the business level.

2.3.3 Critique on TOE model

TOE model has been very successful in describing the correlation of adoption to factors at an organizational level, partly owing to its breadth that allows the selection of the appropriate and relevant constructs for each technology. However, this breadth is also a disadvantage since each researcher is required to find and justify the constructs that each context should contain for the specific technology.

Another disadvantage which is common among the presented psychometric frameworks is that the constructs and the items representing them are usually perception based. While this is useful for items and constructs that relate to perceptions regarding adoption decisions, the assessment of constructs that operationalize an objective state like the digital infrastructure of a business can be problematic. The reason for that is that each person may assess differently the Likert-scale answer for such an item, while the influence on adoption may relate to the objectively measurable state.

Moreover, the TOE model as expressed in relevant literature only sporadically includes measures of usefulness of technological adoption. While Sánchez et al. (2025) and Badghish & Soomro (2024) do refer to usefulness, only in the latter publication is usefulness emphasized.

Finally, the literature studying AI adoption in the Greek case is limited. Quantitative data exist only from state and international organizations as well as some consulting firms. However, there is no study so far (to the best of the writer's knowledge) that performs inferential analysis on the relationship between business factors, specifically the technological context and AI adoption.

2.4 Construct selection

Based on the literature review, this dissertation bases the study of AI adoption in Greek SMEs on the TOE-DOI framework due to its emphasis on the drivers and barriers at the organizational level. AI technologies are highly data-driven and depend on adequate digital infrastructure and information systems. Therefore, the main research question for this thesis

concerns the influence of existing technological capabilities on AI adoption. Thus, the technological context within the TOE-DOI framework was selected to explore this question.

The selected constructs were Infrastructure (T1), IT Knowledge (T2), Data readiness (T3), Compatibility (T4) and Complexity (T5). Data Readiness, while not a canonical TOE-DOI construct, is selected exploratorily due to the highly data-dependent nature of AI systems and due to its consistent identification as a critical enabler and barrier in the relevant literature.

The small set of constructs allows for a more focused research design and questionnaire structure, thus leading to better response quality and lower respondent fatigue.

2.5 Hypotheses formulation

In this research AI adoption was examined through two dependent variables. The first is AI adoption state, which investigates the present state of AI adoption in the business. It is assessed across intensity, frequency and breadth of use. The second dependent variable is AI adoption intention. This variable examines the intention to adopt AI and whether the business is actively planning to adopt AI.

The hypotheses are adapted from the relevant literature to match the Greek SME AI adoption context and the independent and dependent variables.

Infrastructure

Almashawreh et al. (2024) refer to Infrastructure as one of the main pillars for successful AI implementation. Infrastructure enables the AI system implementation, operation and integration with business functions. Well-developed infrastructure fosters innovation, assists the business in creating value and boosts adaptability (Almashawreh et al., 2024). These factors further facilitate adoption and reduce perceived adoption complexity. Conversely, infrastructure inadequacies have been consistently identified as an important barrier to AI adoption in relevant literature (Bérubé et al., 2021; Grünbichler, 2023; Zavodna et al., 2024). Therefore, a business with developed infrastructure is expected to exhibit higher levels of AI adoption. Moreover, adequate infrastructure supports future AI adoption decisions.

H0_{1s}: Infrastructure does not have a statistically significant positive effect on AI adoption state in Greek SMEs (Null Hypothesis).

H1_{1s}: Infrastructure has a statistically significant positive effect on AI adoption state in Greek SMEs (Alternative Hypothesis).

H0_{1i}: Infrastructure does not have a statistically significant positive effect on AI adoption intention in Greek SMEs (Null Hypothesis).

H1_{1i}: Infrastructure has a statistically significant positive effect on AI adoption intention in Greek SMEs (Alternative Hypothesis).

IT Knowledge

Schwaewe et al. (2025) indicate in their literature review that IT Knowledge, encompassing digital skills, is consistently correlated with positive attitudes towards AI. Employees' IT knowledge and capabilities are significant contributors to the successful implementation of AI (Almashawreh et al., 2024) in SMEs. Conversely, lack of IT competence and skills is identified as one of the major barriers to AI adoption (Grünbichler, 2023; Zavodna et al., 2024). Beyond being critical to implementing AI systems, it also contributes to assessing what AI can offer to the business and which AI solutions are preferable (Zavodna et al., 2024). Thus, a business possessing advanced IT Knowledge is expected to exhibit higher AI adoption state. Furthermore, the presence of IT Knowledge should facilitate AI adoption intention by reducing perceived adoption complexity.

H0_{2s}: IT Knowledge does not have a statistically significant positive effect on AI adoption state in Greek SMEs (Null Hypothesis).

H1_{2s}: IT Knowledge has a statistically significant positive effect on AI adoption state in Greek SMEs (Alternative Hypothesis).

H0_{2i}: IT Knowledge does not have a statistically significant positive effect on AI adoption intention in Greek SMEs (Null Hypothesis).

H1_{2i}: IT Knowledge has a statistically significant positive effect on AI adoption intention in Greek SMEs (Alternative Hypothesis).

Data Readiness

Data quality consistently appears in the literature as a determinant for AI adoption (Bérubé et al., 2021; Grünbichler, 2023; Zavodna et al., 2024). Lack of data or poor data quality, specifically is recognized as hindering the implementation of AI, unlike other IT technologies which are less data-dependent (Bérubé et al., 2021). Sánchez et al. (2025) argue that data not only influence AI's effectiveness but also the trust in its results. In essence, AI systems need adequate data to function. Therefore, higher levels of Data Readiness are expected to be associated with higher levels of AI adoption. Moreover, it is expected that data-ready businesses will show higher intention to increase AI adoption because it reduces perceived adoption difficulty.

H0_{3s}: Data Readiness does not have a statistically significant positive effect on AI adoption state in Greek SMEs (Null Hypothesis).

H1_{3s}: Data Readiness has a statistically significant positive effect on AI adoption state in Greek SMEs (Alternative Hypothesis).

H0_{3i}: Data Readiness does not have a statistically significant positive effect on AI adoption intention in Greek SMEs (Null Hypothesis).

H1_{3i}: Data Readiness has a statistically significant positive effect on AI adoption intention in Greek SMEs (Alternative Hypothesis).

Compatibility

Compatibility is the degree to which the technology is aligned with the business's infrastructure, values, procedures and organizational state (Beatty et al., 2001; Badghish & Soomro, 2024). It facilitates AI implementation by requiring fewer changes to existing processes and systems to adopt AI (Badghish & Soomro, 2024). In essence, an AI compatible business is ready to adopt AI requiring minimal changes and therefore at lower cost compared to a less compatible one. Thus, it is expected that high levels of Compatibility will be associated with higher levels of AI adoption. Furthermore, businesses with high levels of compatibility are expected to have higher AI adoption intention due to lower perceived adoption complexity.

H0_{4s}: Compatibility does not have a statistically significant positive effect on AI adoption state in Greek SMEs (Null Hypothesis).

H1_{4s}: Compatibility has a statistically significant positive effect on AI adoption state in Greek SMEs (Alternative Hypothesis).

H0_{4i}: Compatibility does not have a statistically significant positive effect on AI adoption intention in Greek SMEs (Null Hypothesis).

H1_{4i}: Compatibility has a statistically significant positive effect on AI adoption intention in Greek SMEs (Alternative Hypothesis).

Complexity

Complexity refers to the degree to which the owners and employees of a business perceive AI as difficult to understand and use (Beatty et al., 2001; Lin & Ho, 2011; Badghish & Soomro, 2024). A new technology can appear intimidating to the stakeholders involved in its implementation (Beatty et al., 2001). In essence, high perceived AI complexity is expected to discourage decision makers from adopting AI and hinder adoption planning. Thus, Complexity is expected to negatively influence AI adoption levels. Furthermore, perceived AI complexity is expected to be associated with lower levels of AI adoption intention.

H0_{5s}: Complexity does not have a statistically significant negative effect on AI adoption state in Greek SMEs (Null Hypothesis).

H1_{5s}: Complexity has a statistically significant negative effect on AI adoption state in Greek SMEs (Alternative Hypothesis).

H0_{5i}: Complexity does not have a statistically significant negative effect on AI adoption intention in Greek SMEs (Null Hypothesis).

H1_{5i}: Complexity has a statistically significant negative effect on AI adoption intention in Greek SMEs (Alternative Hypothesis).

The conceptual model of the study is presented in figure 3.

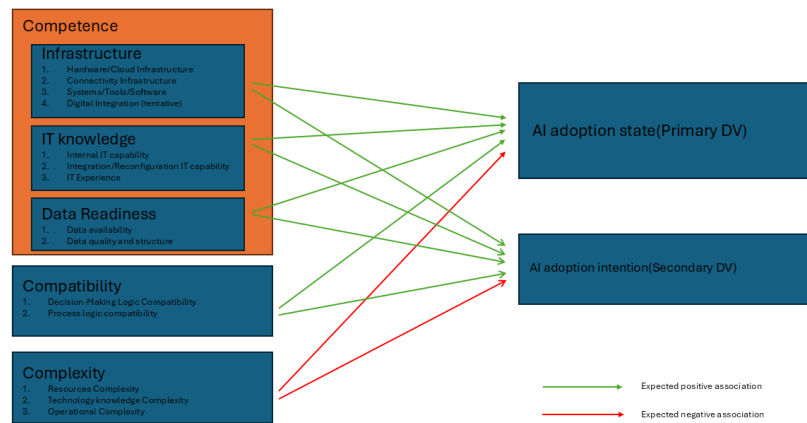


Figure 3. Conceptual Model of the Study.

3. Methodology

3.1 Research design

This dissertation adopts a primary research methodology to assess the relationship between factors influencing AI adoption in SMEs in Greece and AI adoption outcomes. Since the dissertation is based on previously established constructs in relevant literature, the survey is quantitative, aiming to collect data from a suitable sample to provide an empirical assessment of both AI adoption and the influence of technological factors on it. The study is performed at a single point in time, therefore it is cross-sectional. These methodological choices are aligned with the research objectives for this dissertation.

3.2 Theoretical framework and constructs

Drawing on the TOE-DOI framework, this study focuses on the technological context of AI adoption. Prior literature has consistently highlighted the importance of technological factors, and especially technological competence on AI adoption. Specifically, Infrastructure, IT Knowledge and Data Readiness are recognized as critical determinants for AI. The constructs examined in this study are IT infrastructure, IT knowledge, Data Readiness, Complexity and Compatibility. A more compact set of constructs is also expected to result in a more concise questionnaire, reducing respondent fatigue and increasing response rate.

3.3 Questionnaire development

The questionnaire was developed with items based on prior empirical studies. The items' wording was adapted from English to Greek and to the AI adoption context in SMEs where needed. Items that captured observable behavior were preferred to reduce ambiguity in the respondents' answers. Furthermore, some exploratory items were added for supplementary analysis.

For IT Infrastructure the items were sourced from Lin and Lin (2008), Awa and Ojiabo (2016) and Almashawreh et al. (2024) with minor adaptations for context. The items assess the degree to which businesses possess hardware, software and internet connectivity

resources. Furthermore, a group of items assesses the use of the infrastructure across business functions. An additional item assessed the use of the infrastructure for business automation.

Items for IT Knowledge were based on Lin and Lin (2008), Awa and Ojiabo (2016) and Almashawreh et al. (2024) with minor modifications for concreteness and context. These questions assess the employees' knowledge and capability regarding the use, modification and updating of IT systems. The items are designed so that they capture not only the presence of knowledge but also experience in applying that knowledge to assess practical capability.

Data Readiness items are sourced from AI-related literature (Bérubé et al., 2021; Grünbichler, 2023; Zavodna et al., 2024; Sánchez et al., 2025). The questions assess the data storage practices, including both the breadth of data gathered and the frequency of data collection. Furthermore, data quality in terms of data structure and format consistency is assessed. Additional items investigate the utilization of data in selected business functions.

Compatibility items were based on Lin & Ho (2011), Awa & Ojiabo (2016) and Badghish & Soomro (2024) and were minimally adapted for clarity and the AI context. The items assess how well AI systems align with the current business state. The dimensions assessed are compatibility with existing IT systems, existing procedures and the existing organizational culture.

Items for complexity are sourced from Beatty et al. (2001), Lin & Ho (2011) and Badghish & Soomro (2024) with minor adaptations for clarity in the AI context in SMEs. The items assess the respondent's perceived difficulty of learning and using AI. The questions capture how complex the respondent considers understanding AI systems, sharing AI knowledge among employees and the level of necessary specialized experience.

AI adoption state and AI adoption intention are measured through items synthesizing and extending adoption and usage measures in the literature (Awa & Ojiabo, 2016; Almashawreh et al., 2024; Badghish & Soomro, 2024). AI adoption state items assess both how the respondent perceives the business's AI adoption state and the regularity of usage. Moreover, the utilization across business functions is measured which allows for a more detailed assessment of use. These are complemented by a presence-based question for specific AI tools used for descriptive statistics. Furthermore, an ancillary question focusing

on the Greek businesses digitization obligations and the associated data usage opportunities is included. AI adoption intention uses 2 items that measure the intention to increase AI usage and the existence of a strategy for adoption.

Demographic questions were added that capture the number of employees, the annual turnover, the industry sector, the region where the business is based, the existence of IT personnel, the yearly IT budget and the position of the respondent in the business. These items are included for potential post-hoc sample analysis as well as for use as control variables.

3.4 Sampling and data collection

The research was conducted through an online questionnaire. The target population consists of SMEs operating in Greece. Respondents were approached through Greek regional chambers of commerce and trade associations. Mailing lists from these institutions were also used to directly contact businesses. Moreover, mailing lists to HOU students were used to reach professionals employed in SMEs or owning SMEs that study in the MBA program. Additionally, respondents were approached through targeted social media advertisements. The use of multi-channel distribution aimed to improve SME coverage. The respondents were either owners or employees of the businesses and they completed the form based on their knowledge of the firm. The online questionnaire was hosted on Google Forms, while the data collection period was 6 weeks. The form needed 8-10 minutes on average for completion and did not gather personal data that could reliably identify either the respondent or the business they were answering for. The total number of responses gathered was 181, while after data cleaning the valid questionnaires were 172.

The resulting sample is non-probability with characteristics from convenience sampling. Due to the voluntary participation the sample has self-selection characteristics. Therefore, it may exhibit self-selection bias, which can potentially result in higher representation of digitally mature businesses. Moreover, the distribution channel has coverage limitations since even though contacting businesses through the chambers of commerce should in theory reach all businesses equally, many businesses, especially businesses that are in earlier stages of their digital transformation may not receive these newsletters or not frequently access the chambers' webpages. Finally, while using multiple channels of distribution

should increase the coverage, it increases the risk of multiple responses from the same business, which can bias the sample potentially overrepresenting the larger businesses.

3.5 Ethical Considerations

The survey was conducted with voluntary participation of respondents and respondents could stop filling the questionnaire at any point. In the introduction text of the survey, the purpose of the survey and the strict academic nature of the research were stated. The research follows GDPR and basic ethical principles. The questionnaire did not collect private data, or data that may result in easily identifying the respondents or their companies. Data were analyzed in aggregate and stored securely.

3.6 Measurement scale

For the items used for the inferential part of the study 5-point Likert scale was used (Likert, 1932). The scale provides sufficient response granularity while minimizing respondent confusion (Dawes, 2008; Joshi et al., 2015). These studies argue that 5- and 7-point scales are appropriate in most cases and the 5-point Likert has comparable measurement capability with the 7-point one. Apart from being the most used in relevant literature, this scale is appropriate for this dissertation because the nature of the questions in the technology adoption context is such that a more detailed ordinal scale may pose selection difficulty to respondents.

Apart from the items used in factor analysis, binary items assessing the existence (yes/no) of specific technologies were used for descriptive statistics. The demographics items and possible answers were structured to support post-hoc subgroup analysis and to assess the influence on AI adoption of demographic metrics like size and turnover, as well as geographic location.

3.7 Pilot study

A small pilot study was conducted where 5 respondents answered the questionnaire and provided feedback. The purpose of the pilot study was to evaluate the time required for completing it and the clarity of the questions and answers. Moreover, items that may pose

privacy or other unforeseen issues were assessed. The respondents were a mix of experts on primary research and non-expert business employees or owners. This mix served a dual purpose. It allowed for expert consultation on changes necessary to maximize the response accuracy and rates but also provided feedback from respondents that are more representative of the target respondent population. Based on the feedback from the pilot study, the demographic item asking for the years of operation of the business was excluded for privacy reasons, to reduce the possibility of identifying the business. Furthermore, in some items the wording was updated for better comprehension. The actual content of the items was not modified.

3.8 Data analysis methods

For the analysis, the research data first underwent preprocessing using Microsoft Excel. The main analysis phase was performed using IBM SPSS Statistics.

The survey did not allow for submission of incomplete questionnaires since all questions were mandatory. Furthermore, open-ended items were limited to non-inferential items, reducing the risk of invalid responses affecting inference. Moreover, since identical answers can be submitted by different respondents, actual duplicates cannot be reliably identified. Thus, during the preprocessing phase, questionnaires were checked for straight-lining, while minimal additional cleaning was necessary.

First, descriptive statistics were calculated for demographics, individual items, constructs, AI adoption state and AI adoption intention. Pearson correlations analysis was conducted to examine associations between the constructs before factor analysis. Aggregate indicators were created where needed, especially for function-level breadth items to avoid overweighting specific constructs.

To assess the internal consistency of the items within each construct, Cronbach's alpha was employed. A threshold of 0.7 was used, in accordance with the literature (Cronbach, 1951; Tavakol & Dennick, 2011).

Following that, Exploratory Factor Analysis was performed to identify latent structure and assess the correspondence between items and constructs, as well as to identify additional factors not accounted for in the initial hypotheses derived from the literature review (Straub

et al., 2004). Before conducting EFA, the adequacy of the data was tested using the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity to assess the presence of correlations among variables. The factor analysis was conducted using Principal Component Analysis (PCA), which is widely used as an extraction method in similar empirical studies. Additionally, analysis was performed using Principal Axis Factoring (PAF) that is more appropriate for latent factor identification and was used to verify the PCA results. Varimax rotation was applied to improve the interpretability of the factors. The criterion for factor selection was an eigenvalue greater than 1, while items were interpreted as correlated with a specific factor when their loading on the factor was at least 0.4 (Straub et al., 2004). Factor analysis allows for the examination of whether items align with the prescribed constructs and the assessment of potential overlap between constructs. Furthermore, usage-related and existence-related infrastructure items were examined to determine whether they load on the same factor.

After conducting EFA to assess the item-construct alignment, composite variables were constructed by averaging the corresponding items. This approach was adopted because the number of items is not fixed across constructs. For each of the two blocks of questions that examine adoption or use per business function, a single "breadth" variable was produced by averaging the corresponding items. This ensured that infrastructure usage or AI adoption breadth did not disproportionately influence their corresponding constructs relative to other subdimensions.

For the inferential analysis, this thesis employed multiple linear regression analysis. The regression model assumes linear relationships between the independent variables and the dependent variables. Statistical significance was assessed at the 5% level. For each of the dependent variables, AI adoption state and AI adoption intention, a separate regression model was estimated. The independent variables correspond to the constructs of Infrastructure, IT Knowledge, Data Readiness, Compatibility and Complexity. The dependent variables were operationalized as composite indices derived from the corresponding items. Furthermore, multicollinearity among independent variables was assessed using the Variance Inflation Factor (VIF).

4 Results

4.1 Cleaning and preparation

The study was conducted through an online questionnaire. 181 responses were gathered. Since the questionnaire allowed for non-SMEs responses, firm size was used as a filtering criterion to reject responses with 250 or more employees or with “Do not Know/Do not answer”. While the EU definition for SMEs also contains an annual turnover criterion and there was a relevant question in the questionnaire, it was not used for filtering because it is information that not all firm members possess. Thus, there were many “Do not know/ Do not answer responses”. Moreover, even though the survey was completely anonymous there remained a possibility that some firm owners and employees would not like to disclose this information. Table 2 presents the results for the number of employees. Cleaning according to this criterion led to the rejection of 9 responses, thus producing 172 valid answers.

Table 2. Number of employees distribution.

Employee(s) number	Frequency	Percent
>250	6	3.3
0-9	117	64.6
10-49	44	24.3
50-249	11	6.1
Do not know/ Do not answer	3	1.7
Total	181	100.0

No responses were excluded solely based on straight-lining, since identical answers may represent legitimate perceptions. However, the results were checked for responses claiming high AI adoption but not using AI in any function of the business. This test did not identify any clearly invalid responses.

4.2 Descriptive statistics

This section presents the basic descriptive analysis of key demographic variables, while more data are presented in Appendix B. The most important characteristics are the Firm Size (Table 3), Business Sector (Table 4) and Region (Table 5).

Table 3. Frequencies and percentages of firm size categories in the survey's sample.

Firm Size Category (employee number)	Frequency	Percent
0-9	117	68.0
10-49	44	25.6
50-249	11	6.4
Total	172	100.0

Table 4. Frequencies and percentages of firm sectors in the survey's sample.

Business Sector	Frequency	Percent
Services	40	23.3
Tourism/Hospitality	36	20.9
Retail/Trade	33	19.2
Manufacturing	26	15.1
Agri-food	12	7.0
Technology	10	5.8
Construction	9	5.2
Logistics (Supply Chain)	4	2.3
Other	2	1.2
Total	172	100.0

Table 5. Frequencies and percentages of firm location in the sample of the survey.

Region	Frequency	Percent
Attica	47	27.3
Western Greece	23	13.4
Central Macedonia	18	10.5
Peloponnese	15	8.7
Thessaly	14	8.1
Epirus	9	5.2
Central Greece	8	4.7
Western Macedonia	7	4.1
Ionian Islands	7	4.1
Crete	7	4.1
Eastern Macedonia & Thrace	6	3.5
North Aegean	6	3.5
South Aegean	5	2.9
Total	172	100.0

While for the purposes of this dissertation there was no extensive effort to match the actual SME size category, region and business sector distribution of the sample has representatives from most sectors and all regions and the firm-size distribution is reasonable. The micro businesses dominated the sample with almost 70% of the total while the small businesses were around 26% and the medium businesses around 6%. Attica as expected was the region

with the highest number of responses. The more urbanized regions (Attica, Central Macedonia, Western Greece) accounted for 51.2% of the responses. Regarding business sectors, Services, Tourism/Hospitality and Retail/Trade accounted for over 60% of the total sample.

In table 6 the items are categorized with their variable names, the construct they belong to, a brief description and their mean and standard deviation values. Mean and standard deviation are presented only for Likert coded items. The original Greek items and their English translations are presented in Appendix A.

Table 6. Items of the survey, construct category, and descriptive statistics.

Variable	Construct*	Brief Description	Mean	Stdev
INF1	INF	Have adequate digital infrastructure	3.40	1.158
INF2	INF	Have adequate server or cloud infrastructure	2.99	1.481
INF3	INF	Have adequate internet connection	3.62	1.244
-	NI	Digital tools the firm uses		
INF4_1	INF	Digitalization level: Main Activity	2.53	1.531
INF4_2	INF	Digitalization level: Supplies and Inventory	2.30	1.330
INF4_3	INF	Digitalization level: Finance and Accounting	3.24	1.086
INF4_4	INF	Digitalization level: Sales/e-shop/ orders	2.42	1.533
INF4_5	INF	Digitalization level: Marketing	2.85	1.355
INF4_6	INF	Digitalization level: Customer service	2.70	1.443
INF4_7	INF	Digitalization level: Data analysis for business decisions	1.82	1.217
DAT1	DAT	Use social media analytics for marketing strategy	1.90	1.153
DAT2	DAT	Use CRM/ERP data for targeted marketing	1.81	1.094
INF5	INF	Use basic automation (Reminders, etc)	2.40	1.336
ITKN1	ITKN	Have adequate IT Knowledge to use systems	2.92	1.263
ITKN2	ITKN	Have adequate IT Knowledge (internal or external) to install or parameterize systems	2.74	1.362
ITKN3	ITKN	Have installed or upgraded digital systems in the last 5 years	2.78	1.357
DAT3	DAT	Use of digital systems to collect and store data about firm's operation	2.52	1.395
DAT4	DAT	They collect and store data in a frequent and regular way	2.34	1.352
DAT5	DAT	They store data in an organized and structured way	2.21	1.334
COMPA1	COMPA	Adopting AI systems in existing IT systems is easy.	2.15	1.145
COMPA2	COMPA	AI systems are compatible with the firm's processes.	2.17	1.205
COMPA3	COMPA	AI systems are compatible with organizational culture and values of the firm	2.35	1.212
COMPL1	COMPL	Understanding AI is difficult	3.58	1.237
COMPL2	COMPL	Sharing knowledge about AI is difficult	3.84	1.236
COMPL3	COMPL	Using AI requires expert knowledge	4.06	1.074
AIS1	AIS	Firm is at an advanced AI adoption state	2.09	1.144
AIS3	AIS	Firm uses regularly AI systems	1.88	1.166
-	NI	Use of myData/POS data for analysis	1.59	1.075

Variable	Construct*	Brief Description	Mean	Stdev
AIS2_1	AIS	AI level of use on supplies	1.42	0.858
AIS2_2	AIS	AI level of use on production/services (main activity)	1.78	1.300
AIS2_3	AIS	AI level of use on RD	1.77	1.344
AIS2_4	AIS	AI level of use on Inventory	1.41	0.878
AIS2_5	AIS	AI level of use on Finance/Accounting	1.49	0.895
AIS2_6	AIS	AI level of use on Sales/E-shop/Orders	1.46	0.933
AIS2_7	AIS	AI level of use on Marketing	2.56	1.452
AIS2_8	AIS	AI level of use on Customer Service	1.97	1.259
AIS2_9	AIS	AI level of use on HR	1.31	0.720
AIS2_10	AIS	AI level of use on Internal Communication	1.53	1.073
AIS2_11	AIS	AI level of use on Data Analysis for Business Decisions	1.64	1.159
-	NI	AI tools that you used last year		
AII1	AII	Firm intends to start or expand AI usage in the next 12-24 months	2.63	1.360
AII2	AII	Firm has AI strategy or assesses AI options	2.15	1.329
DEM1	DEM	Industry sector		
DEM2	DEM	Number of Employees		
DEM3	DEM	Annual Turnover		
DEM4	DEM	Region		
DEM5	DEM	Existence of IT personnel (internal or external)		
DEM6	DEM	Annual IT budget		
DEM7	DEM	Position in the firm		

** INF: Infrastructure, ITKN: IT Knowledge, DAT: Data Readiness, COMPA: Compatibility, COMPL: Complexity, AIS: AI adoption state, AII: AI adoption intention, NI: not used in inference, DEM: Demographics*

Some notable observations in Table 6 are that digital infrastructure (INF1) and internet connection (INF3) exhibit a mean above 3, suggesting at least a basic infrastructure level on average among Greek SMEs. IT Knowledge item means are below 3 but close to it, suggesting lower knowledge level than infrastructure but not at a zero level. The highest mean among digitalization level of business functions is for Finance and Accounting at 3.24, possibly owing to the tax law requirements in Greece. On average Data Readiness items exhibit lower means than Infrastructure and IT knowledge items possibly indicating less developed data practices compared to the state of the other competence factors. Data Readiness items that explicitly contain data utilization have the lowest means, suggesting that even the existing data may not be utilized in business operations. Digitalization level across business functions suggests a similar conclusion. Excluding Finance and Accounting, which is at a comparable level to INF1-3 means, digitalization exhibits lower means. This

could suggest that businesses may not maximize their investment in Infrastructure and IT knowledge to actively digitalize their business functions. Compatibility items exhibit relatively low means at slightly above 2, suggesting that on average Greek SMEs do not perceive themselves as sufficiently prepared and aligned for AI adoption. Likewise, Complexity items have relatively high means suggesting that Greek SMEs perceive AI technologies as difficult to use and requiring expert knowledge. As expected from the literature AI adoption state items have very low means, suggesting that very few Greek SMEs have achieved significant utilization and integration of AI technologies. The highest AI usage mean among business functions is in Marketing at 2.56 which could be attributed to the use of GenAI for digital and general marketing advice. AI adoption intention item means are slightly higher than the state means but still below 3, which might suggest that on average businesses not only have not significantly adopted AI but may also be hesitant to adopt AI technologies.

For subsequent use, two aggregate indices are created for the items that pertain to usage across business functions. As discussed in the Methodology chapter, the averaging avoids overweighting this subdimension within the total constructs but also allows for more balanced assessment among businesses belonging to different sectors. For instance, a software company will need to be digitalized in its main activity but may not have significant inventory activities and report no or low digitalization in this function. Conversely, a retail or manufacturing company is likely to prioritize inventory digitalization. By using the aggregate mean differences are more likely to be smoothed and the index is assumed to be more comparable across sectors. The aggregate indices are INF4 which is the mean of INF4_1 to INF4_7 and AIS2 which is the mean of AIS2_1 to AIS2_11.

After creating the construct variables, the mean, standard deviation as well as the Pearson correlations were calculated, and they are presented in Table 7.

Table 7. Mean, Standard Deviation and Pearson Correlations for the variables (constructs) of the study.

Variables	Mean	Std. Deviation	Pearson Correlations						
			INF	ITKN	DAT	COMPA	COMPL	AIS	AII
INF	2.9909	1.07738	1	.832**	.813**	.692**	-.523**	.685**	.697**
ITKN	2.8140	1.21674	.832**	1	.747**	.685**	-.502**	.695**	.680**
DAT	2.1570	1.08051	.813**	.747**	1	.706**	-.493**	.729**	.734**
COMPA	2.2229	1.12046	.692**	.685**	.706**	1	-.619**	.839**	.770**

Variables	Mean	Std. Deviation	Pearson Correlations						
			INF	ITKN	DAT	COMPA	COMPL	AIS	AII
COMPL	3.8256	1.08893	-.523**	-.502**	-.493**	-.619**	1	-.615**	-.538**
AIS	1.8777	0.98797	.685**	.695**	.729**	.839**	-.615**	1	.874**
AII	2.3895	1.24816	.697**	.680**	.734**	.770**	-.538**	.874**	1

**** Correlation is significant at the 0.01 level (2-tailed)**

Table 7 confirms the conclusions that the item level analysis reached. The mean value of Infrastructure is approximately 3, suggesting a moderate infrastructure level among SMEs, while IT Knowledge is at 2.81 and Data Readiness exhibits an average value of 2.16. This supports the assessment that Infrastructure is more developed, IT Knowledge follows and Data Readiness has the lowest mean among competence dimensions. Compatibility has a relatively low mean of 2.22 and Complexity has a mean of 3.83. Both agree with the comments from the per-item assessment. AI adoption state mean is 1.88 suggesting very low adoption of AI in Greek SMEs, while AI adoption intention is a little higher, with a mean of 2.39. This suggests that even though SMEs are hesitant to adopt AI, they exhibit some interest at a higher level than their current adoption. The most important observation from Table 7 is that all variables exhibit significant correlations among them. Infrastructure, IT Knowledge and Data Readiness have Pearson correlation above 0.7, while compatibility has strong correlation with them above 0.6. Complexity has moderate negative correlations with them, while it has a correlation of -0.62 with Compatibility. These facts may suggest that the constructs are not independent latent factors. AI adoption state and intention are correlated with all constructs with the strongest correlations with Data Readiness and Compatibility. AI adoption state and intention are, as expected, significantly correlated with each other with a correlation of 0.874.

Before proceeding to the inferential analysis Table 8 presents the AI adoption state and AI adoption intention means across firm size categories. The means increase with firm size which is consistent with statistical data from the literature. Literature findings suggest a doubling of AI use from micro to small and another doubling from small to medium. In the survey's data the trend is there but with smaller changes but the use of a 5-point Likert scale and the fact that these data are based on perceptions may smooth the observed differences. AI adoption intention exhibits a similar trend and the mean for intention is in each case higher than the mean for the state which is theoretically expected.

Table 8. AI adoption state and intent means as a function of the number of employees (company size).

Number of Employees	AI adoption state (AIS)			AI adoption intention (AII)		
	Mean	N	Std. Deviation	Mean	N	Std. Deviation
0-9	1.6392	117	0.89628	2.0427	117	1.06991
10-49	2.2314	44	0.87129	3.0114	44	1.24587
50-249	3.0000	11	1.22748	3.5909	11	1.41100
Total	1.8777	172	0.98797	2.3895	172	1.24816

4.3 Reliability

Following descriptive statistics, a reliability analysis was performed to assess the internal consistency of the constructs which were identified in the literature review (Table 9).

Table 9. Cronbach's α analysis results.

Construct	Number of Items	Cronbach's α
Infrastructure	5	0.910
IT Knowledge	3	0.904
Data Readiness	5	0.904
Compatibility	3	0.939
Complexity	3	0.908
AI adoption State	3	0.923
AI adoption Intention	2	0.840

All the constructs demonstrated strong internal consistency with Cronbach's α values substantially exceeding the commonly accepted threshold of 0.7. Moreover, AI adoption state and AI adoption Intention which are the dependent variables were also tested for Reliability and demonstrated strong internal consistency. These results support the specific operationalization choice.

4.4 Exploratory factor analysis

To assess the latent structure of the questionnaire items, an exploratory factor analysis was performed. For the factor analysis both Principal Component Analysis (PCA) and Principal Axis Factoring (PAF) were used. While PCA is a data reduction technique which tries to explain total variance and PAF is a factor analysis method that is used to extract latent factors they often produce similar structures and PCA is more common in the relevant literature.

Initially, a Kaiser-Meyer-Olkin (KMO) measure and a Bartlett's test of sphericity were performed to assess whether the items share enough common variance for a meaningful factor analysis and sufficient correlations exist among the items. The results appear in Table 10, with KMO at 0.93 being substantially above the commonly accepted limit of 0.6 and Bartlett's test being significant ($p < 0.001$), indicating significant correlations between items and thus suggesting the suitability of factor analysis and the possible existence of latent constructs.

Table 10. Kaiser-Meyer-Olkin and Bartlett's test of sphericity results.

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.930
Bartlett's Test of Sphericity	Approx. Chi-Square	3353.435
	df	171
	Sig.	0.000

PCA and PAF were performed using Varimax rotation. Table 11 presents the eigenvalues as well as percentage of variance explained by the factors exhibiting eigenvalues above 1 according to Kaiser's criterion. Both methods indicate similar results. They suggest the existence of 3 factors with the first factor having a substantially larger eigenvalue at 11.33, explaining almost 60% of the total variance before rotation. The second and third factors exhibit eigenvalues between 1 and 2 and they explain approximately 9% and 6% of variance. These results indicate that there is a dominant factor that captures a large proportion of the common variance. Rotation redistributes the explained variance among factors, increasing second and third factors' interpretability. Scree plots presented in figures 4 and 5 for PCA and PAF indicate that the elbow is at the second factor while the first factor dominates. Factors beyond the third contribute only marginal additional variance.

Table 11. PCA and PAF Eigenvalues and Variance explained.

Total Variance Explained									
Principal Component Analysis									
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	11.330	59.629	59.629	11.330	59.629	59.629	6.291	33.112	33.112
2	1.779	9.364	68.993	1.779	9.364	68.993	4.589	24.154	57.265
3	1.101	5.797	74.789	1.101	5.797	74.789	3.330	17.524	74.789

Principal Axis Factoring									
Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	11.330	59.629	59.629	11.050	58.156	58.156	6.056	31.876	31.876
2	1.779	9.364	68.993	1.538	8.097	66.253	4.263	22.436	54.312
3	1.101	5.797	74.789	0.753	3.961	70.214	3.021	15.902	70.214

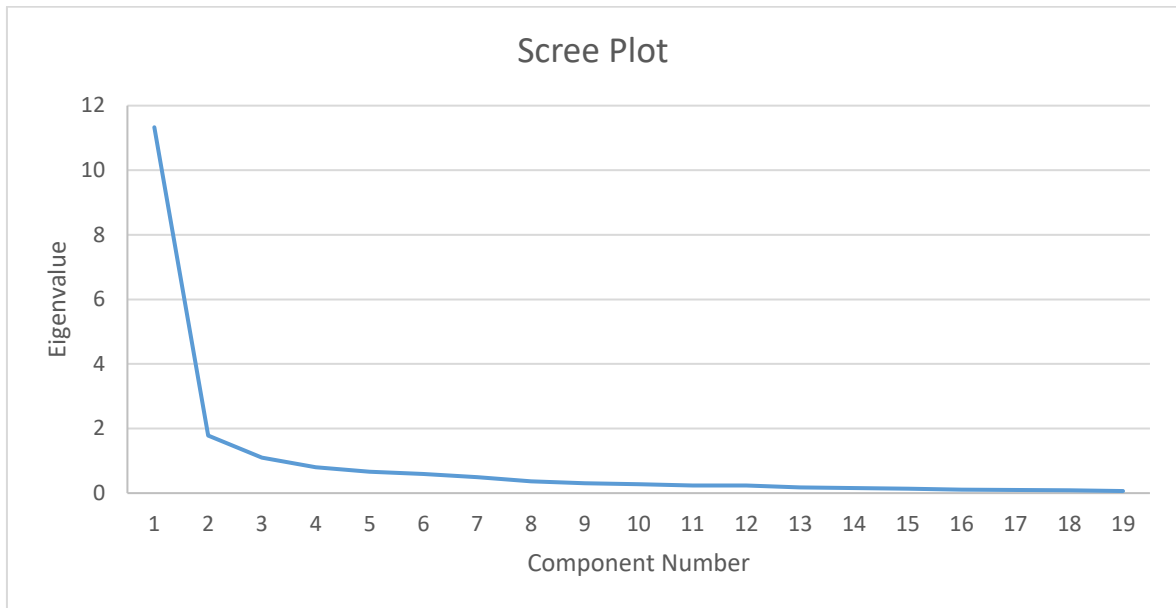


Figure 4. Scree Plot of PCA.

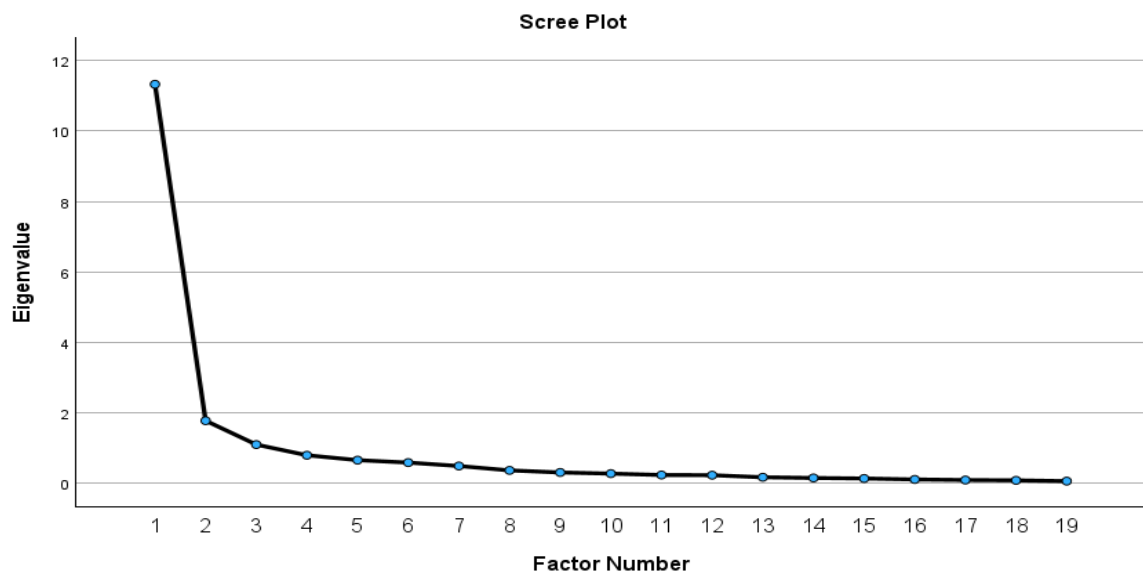


Figure 5. Scree plot for PAF.

Table 12. Item Loading to Factors for PCA and PAF (loadings below 0.4 were discarded).

Items	PCA results after rotation			PAF results after rotation		
	Factor 1	Factor 2	Factor 3	Factor 1	Factor 2	Factor 3
INF1	0.862			0.854		
INF2	0.79			0.745		
INF3	0.776			0.695		
INF4	0.697	0.565		0.704	0.550	
INF5	0.622	0.523		0.614	0.498	
ITKN1	0.723			0.701		
ITKN2	0.735			0.714		
ITKN3	0.695			0.640		
DAT1		0.654			0.470	
DAT2		0.751			0.607	
DAT3	0.713	0.551		0.718	0.534	
DAT4	0.651	0.606		0.660	0.582	
DAT5	0.618	0.617		0.624	0.591	
COMPA1		0.665	0.502		0.693	0.448
COMPA2		0.649	0.459		0.687	0.412
COMPA3		0.645	0.439		0.666	
COMPL1			-0.858			-0.841
COMPL2			-0.844			-0.816
COMPL3			-0.835			-0.747

Analysis of the loadings results is presented in Table 12. INF1, INF2 and INF3 which are traditional TOE Infrastructure items and ITKN1, ITKN2 and ITKN3 which are traditional TOE IT Knowledge items load mainly on factor 1. Dominant loading on factor 1 exists also for DAT3, DAT4 and DAT5 which are traditional Data readiness items derived from relevant literature as discussed in the Questionnaire development section. This would indicate that the first factor may represent a broader technological competence dimension as discussed in TOE literature, consisting of tangible and intangible resources. Moreover, it appears to partially include data readiness, possibly the part that assesses data as a resource and not their utilization. DAT1 and DAT2 load primarily on the second factor, while strong loadings on this factor are exhibited by INF4, and INF5, DAT3 to DAT5 and COMPA1 to COMPA3. COMPA1 to COMPA3 load on the third factor too. DAT1 and DAT2 are items discussing the usage of data for decisions, DAT3 to DAT5 are classical data readiness questions that by their nature encompass the manipulation of data, INF4 asks about the use of digital systems in firm functions and INF5 is also about using systems for automation. Compatibility items assess the compatibility of AI with the company's systems, procedures,

organization and values. This may also partially reflect AI readiness. Thus, the second factor likely encompasses the use of digital systems and data in the business and the readiness of the business to adopt AI. Therefore, it may represent the Digital Utilization and AI readiness of the firm. The third factor seems to correspond to the DOI factor of complexity mainly since the complexity-related items load strongly to this factor only and compatibility questions load partially to it also. The reason for compatibility's loading on the factor could be that a strong AI compatibility perception could lead to lower perceived complexity, which may explain the relationship between the constructs.

Both PCA and PAF provide comparable results with PAF providing slightly better distinction in the item loadings among factors. Comparing the factors with the literature derived factors Infrastructure and IT Knowledge which are traditional TOE technological constructs seem to correspond to the same variable for the survey's sample. Data Readiness is also important and loads partly in the same factor. Digital Utilization and AI readiness encompassing Digital systems use, Data utilization and AI Compatibility exhibit a distinct factor behavior, while complexity which is a DOI construct is also a distinct factor. The loadings of Infrastructure, IT knowledge and data in one factor may support that SMEs consider the technological resources holistically and not as distinct aspects. At the same time actual utilization and integration of the resources for the needs of the business appear to be perceived as a distinct variable.

Moreover, an additional exploratory analysis was conducted using only the traditional TOE-DOI items (Infrastructure, IT Knowledge, Compatibility, Complexity), excluding pure usage items (INF4 and INF5) and all the data readiness items to assess whether their existence changes the results of factor analysis. The results, however, did not produce a separation between the 4 constructs but produced a factor which combined Infrastructure, IT Knowledge clearly and part Compatibility, which also exhibited cross-loadings with the Complexity factor. This gives an even stronger indication that at least for the sample of this survey SME respondents may perceive the Technological Competence and AI readiness as an integrated concept and not as distinct factors.

4.5 Regression for AI adoption state

The results from EFA suggest a latent structure of three factors, which would suggest the use of this structure for regression. Due to the correlations and cross-loadings, the use of separate constructs may create multicollinearity problems. Moreover, the EFA with the traditional items provided substantial convergence between the technological competence/readiness items. On this basis, the regression analysis was performed using two different models. For the first model, which is theory driven, the items were combined into independent variables as originally hypothesized, with the variables being Infrastructure, IT Knowledge, Data Readiness, Compatibility and Complexity. The second model was empirically motivated by the EFA analysis results. For this model, the constructs corresponding to EFA factors identified as Technological Competence and Digital Utilization and AI Readiness were combined to create the variable of Digital State and AI Readiness which describes the general state and utilization of digital resources and the readiness of the firm to adopt AI systems. This empirical variable partially overlaps with concepts associated with digital maturity.

4.5.1 Initial constructs regression for AI adoption state

The regression analysis with the original constructs exhibits an R of 0.870 (Table 13) and an Adjusted R² of 0.750, which indicate strong explanatory power of the independent variables. Table 14 presents the ANOVA results, which suggest that the overall model is statistically significant ($F=103.4$, $p<0.001$). The Durbin-Watson statistic of 1.614 does not indicate problematic autocorrelation. Figures 6, 7 and 8 present the Histogram, Normal P-P plot and residual scatterplot. These figures did not indicate major deviations from normality or linearity and there is no obvious pattern to suggest significant heteroscedasticity.

Table 13. Summary for the AI adoption state regression model with the original variables.

Model Summary				
R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
.870	0.757	0.750	0.49427	1.614

Table 14. ANOVA results for the AI adoption state regression model with the original variables.

ANOVA					
	Sum of Squares	df	Mean Square	F	Sig.
Regression	126.354	5	25.271	103.439	<.001
Residual	40.555	166	0.244		
Total	166.909	171			

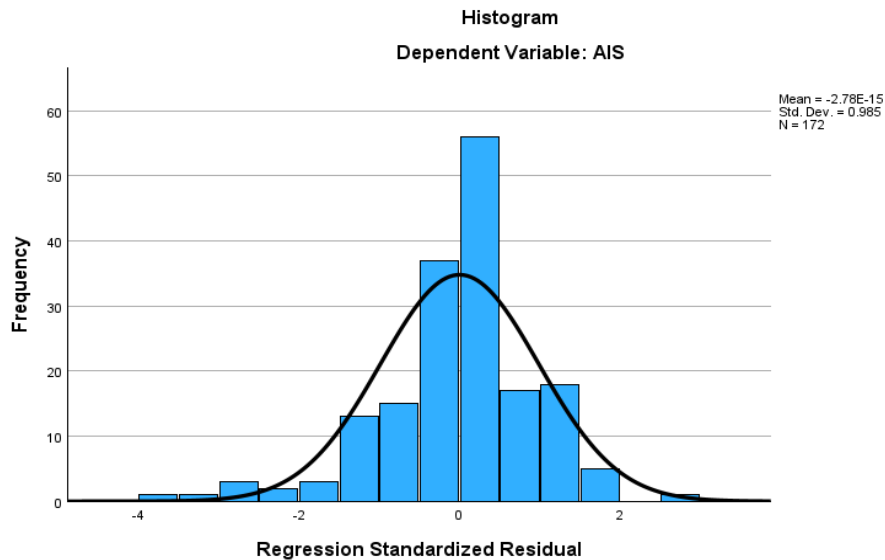


Figure 6. Histogram of Residuals for the original construct regression case.

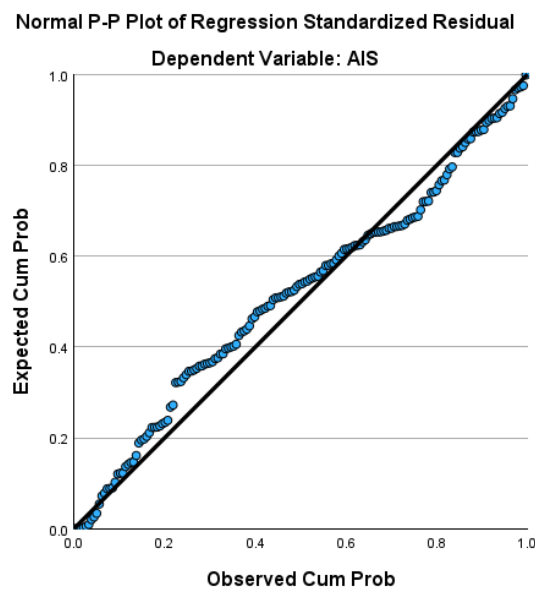


Figure 7. Normal P-P plot of residuals for the original construct regression case.

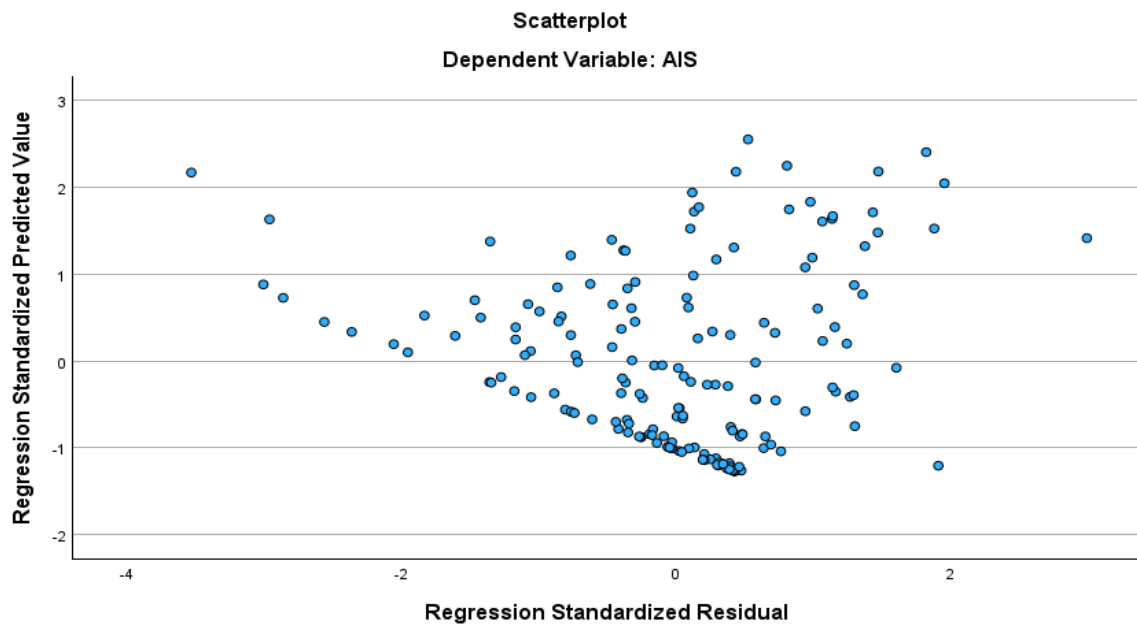


Figure 8. Residual Scatterplot for the original construct regression case.

Table 15. Regression Coefficients for the original construct case.

Variable	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity
	B	Std. Error	Beta			VIF
(Constant)	0.639	0.269		2.373	0.019	
INF	-0.049	0.075	-0.053	-0.648	0.518	4.552
ITKN	0.108	0.059	0.132	1.831	0.069	3.579
DAT	0.203	0.065	0.222	3.144	0.002	3.408
COMPA	0.485	0.055	0.551	8.792	0.000	2.680
COMPL	-0.114	0.045	-0.126	-2.540	0.012	1.670

Table 15 presents the coefficients of the model as well as the t-statistics and significance, combined with other statistics. Using a significance threshold of 0.05 for the t-test the variables with statistically significant coefficients are Data Readiness, Compatibility and Complexity, while for IT Knowledge $p=0.069$ slightly above the significance threshold. Infrastructure does not exhibit statistical significance in the model. These results indicate a strong association of AI adoption state with Compatibility and Data Readiness, as well as a significant association with Complexity. Moreover, Compatibility exhibits the largest standardized coefficient at 0.551 indicating the importance of its association to AI adoption state. The coefficients for Data and Compatibility are positive, consistent with theoretical expectations, and the coefficient for Complexity is negative which is consistent with its

theoretical role as a barrier. While the significance of IT Knowledge is small and Infrastructure is not statistically significant this may not actually contradict literature but imply an indirect contribution. Data, IT Knowledge and Infrastructure exhibit VIF values above 3 which indicate moderate multicollinearity. From a theoretical standpoint data readiness requires both the existence of appropriate infrastructure and of knowledge of use of IT systems. Moreover, Infrastructure and IT Knowledge even though they are prerequisites they may not be enough for AI adoption and this contributes to their low significance. These findings are also consistent with the EFA results.

4.5.2 Aggregate construct regression for AI adoption state

Since the factor analysis indicated strong cross-loadings and the existence of a dominant factor as well as the multicollinearity indications, the use of a model operationalizing the Digital State and AI Readiness as one independent variable is a reasonable choice. The variable is constructed as the mean of Infrastructure, IT Knowledge, Data Readiness and Compatibility, keeping Complexity as the second independent variable. Thus, the broader technological readiness factors that positively affect AI adoption were grouped together while the barrier of Complexity remained a distinct dimension. Averaging was performed at the construct level and not the individual items' level so that each subdimension is weighted equally even though they contain different numbers of items.

Table 16. Summary for the AI adoption state regression model with the aggregate variables.

Model Summary				
R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
.834	0.696	0.692	0.54797	1.900

Table 17. ANOVA results for the AI adoption state regression model with the aggregate variables.

ANOVA					
	Sum of Squares	df	Mean Square	F	Sig.
Regression	116.163	2	58.081	193.428	<.001
Residual	50.746	169	0.300		
Total	166.909	171			

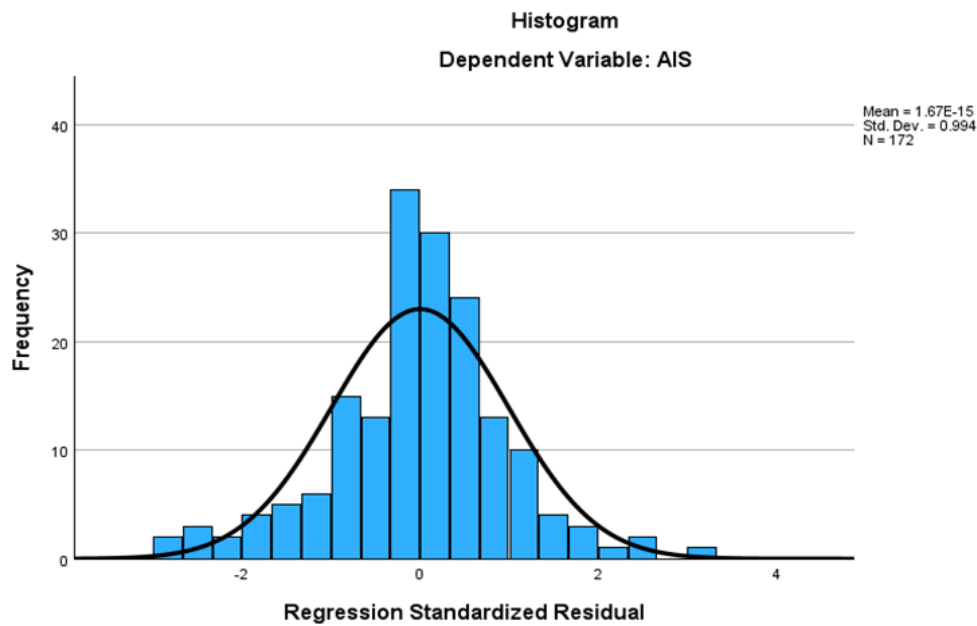


Figure 9. Histogram of Residuals for the aggregate construct regression case.

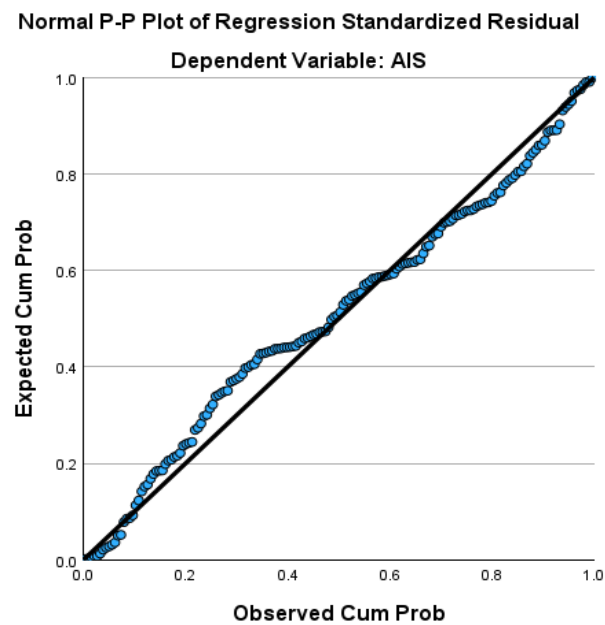


Figure 10. Normal P-P plot of residuals for the aggregate construct regression case.

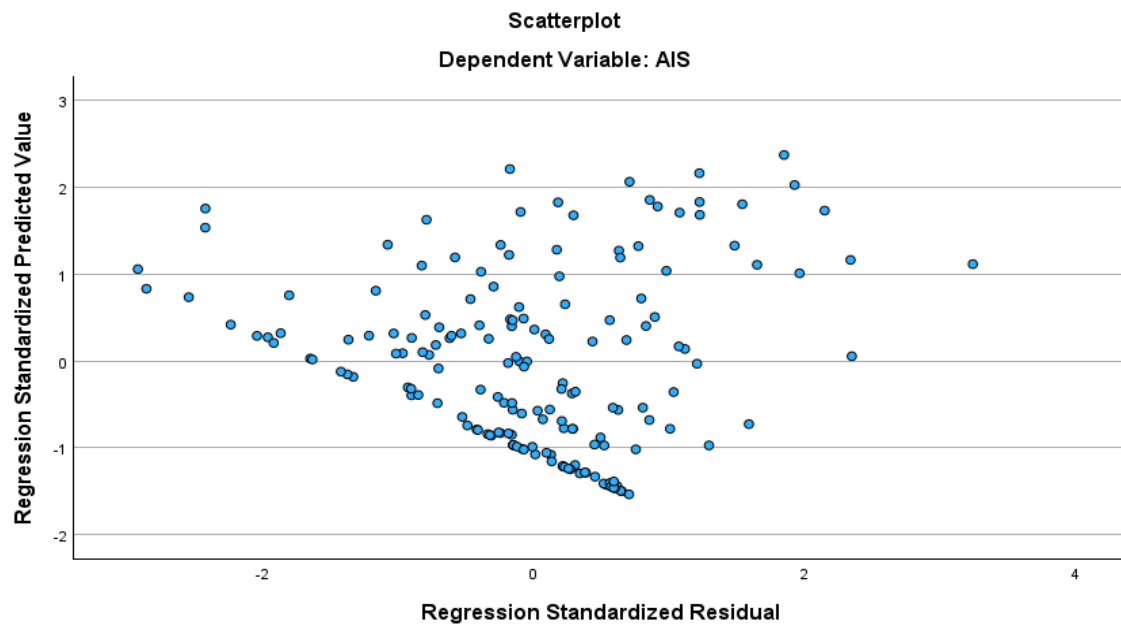


Figure 11. Residual Scatterplot for the aggregate construct regression case.

This model exhibits an R of 0.834 and Adjusted R² of 0.692 (Table 16), which are slightly lower values than the previous model, but its explanatory power remains strong. ANOVA (Table 17) suggests that this model is also statistically significant ($F=193.4$, $p<0.001$). Moreover, the Durbin-Watson statistic indicates almost no autocorrelation of the residuals with a value of 1.9. Figures 9 to 11 present the Histogram, Normal P-P plot and the residual scatterplot. These graphs suggest that there are no major deviations from normality or linearity. Moreover, no obvious patterns suggesting strong heteroscedasticity are observed.

Table 18. Regression Coefficients for the aggregate case (AI adoption state).

Variable	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics
	B	Std. Error	Beta			VIF
(Constant)	0.825	0.284		2.901	0.004	
COMPL	-0.181	0.048	-0.199	-3.776	0.000	1.544
DigStateAndAIreadiness	0.685	0.051	0.701	13.296	0.000	1.544

For the aggregate model both coefficients are statistically significant at $p<0.001$ (Table 18). Moreover, the VIF values are at 1.544 which suggest low multicollinearity between the two predictors. For that reason, despite the slightly lower explanatory power (R square is about 0.06 lower) this model may better capture the broader readiness dimension, while being

simpler and showing lower multicollinearity. It should be noted that in this model Digital State and AI Readiness exhibits the largest standardized beta (0.701) which is consistent with the previous model result since it incorporates Compatibility and Data Readiness which had the largest betas in that model. The Complexity coefficient in this model appears larger which can be attributed to reduced overlap with the other variable.

4.6 Regression for AI adoption intention

Regression analysis for the dependent variable AI adoption intention was performed following the same methodology as the analysis for AI adoption state.

4.6.1 Initial constructs regression for AI adoption intention

The regression analysis for the dependent variable AI adoption intention exhibits an R value of 0.822 and an adjusted R Square value of 0.665 (Table 19). These values indicate that the model has relatively strong explanatory power. The Durbin-Watson statistic at 1.886 does not indicate problematic autocorrelation. The ANOVA results in table 20 exhibit an F statistic of 69 and $p < 0.001$ which indicates that the model is statistically significant. Figures 12 to 14 present the Histogram, Normal P-P plot and residual scatterplot. From these, no obvious deviations from normality or linearity emerge and they do not suggest significant heteroscedasticity.

Table 19. Summary for the AI adoption intention model with the original variables.

Model Summary				
R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
.822	0.675	0.665	0.72209	1.886

Table 20. ANOVA results for the AI adoption intention regression model with the original variables.

ANOVA					
	Sum of Squares	df	Mean Square	F	Sig.
Regression	179.847	5	35.969	68.985	<.001 ^b
Residual	86.554	166	0.521		
Total	266.401	171			

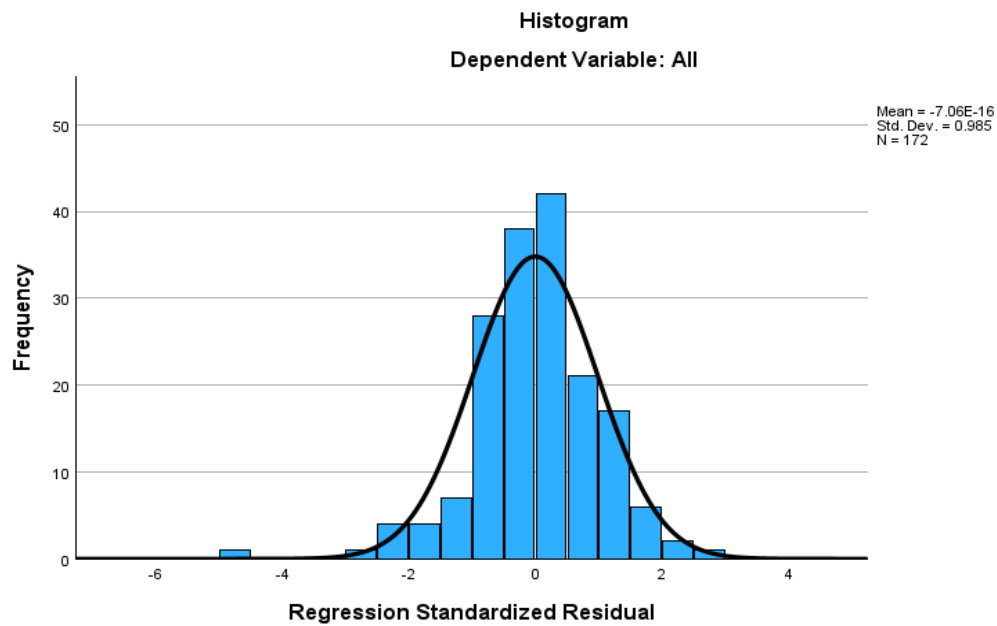


Figure 12. Histogram of Residuals for AI adoption Intention for the original construct regression case.

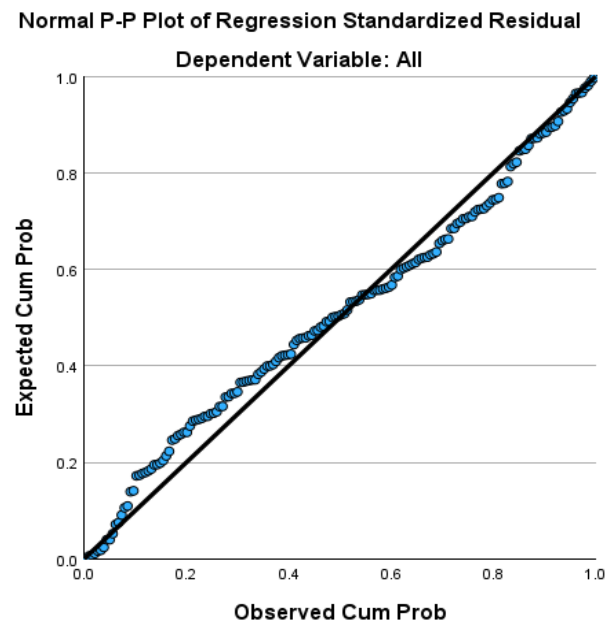


Figure 13. Normal P-P plot of residuals for AI adoption intention for the original construct regression case.

The scatterplot exhibits diagonal lines which imply some structure but this can be attributed to the use of 5-point Likert scale data instead of truly continuous variables. This is much more obvious for the variable of AI adoption intention because it is the mean of 2 Likert

scales which results in a coarsely quantized result scale with 0.5 quantization step from 1 to 5. This is common in relevant research and should not severely impact the validity of the regression.

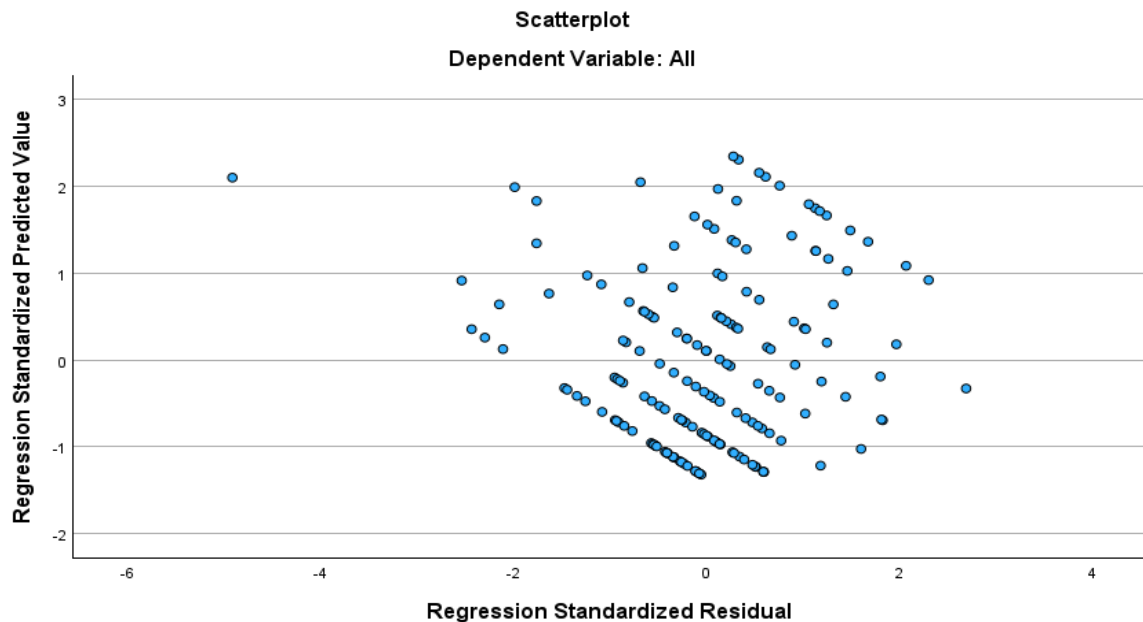


Figure 14. Residual Scatterplot for AI adoption intention for the original construct regression case.

Table 21. Regression Coefficients for AI adoption intention for the original construct case.

Variable	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics
	B	Std. Error	Beta			VIF
(Constant)	0.361	0.393		0.918	0.360	
INF	0.072	0.109	0.062	0.661	0.510	4.552
ITKN	0.099	0.086	0.096	1.152	0.251	3.579
DAT	0.326	0.094	0.282	3.454	0.001	3.408
COMPA	0.478	0.081	0.429	5.927	0.000	2.680
COMPL	-0.060	0.066	-0.053	-0.923	0.357	1.670

In Table 21 the predictors exhibiting statistical significance at a 5% level are Data Readiness and Compatibility. In contrast, Infrastructure, IT Knowledge and Complexity do not show statistical significance according to the t-test. Compared to the AI adoption state model, Complexity loses statistical significance. Compatibility exhibits the largest standardized beta at 0.43 while Data Readiness also exhibits a standardized beta of 0.28. As expected, the VIF values are identical to the corresponding AI adoption state model, since multicollinearity depends only on the relationships among the independent variables. The

results may suggest that compared to AI adoption state, the intention is more associated with the broad digital state than the perceived complexity. This can be theoretically explained by the fact that intention to adopt or expand AI may exist irrespective of the perceived complexity, while Complexity appears more associated with the success of the actual implementation.

4.6.2 Aggregate construct regression for AI adoption intention

Regression analysis for the dependent variable AI adoption intention was performed following the same methodology as the analysis for AI adoption state.

Table 22. Summary for the AI adoption intention regression model with the aggregate variables.

Model Summary				
R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
.804	0.646	0.642	0.74726	1.993

Table 23. ANOVA results for the AI adoption intention regression model with the aggregate variables.

ANOVA					
	Sum of Squares	df	Mean Square	F	Sig.
Regression	172.033	2	86.016	154.043	<.001
Residual	94.368	169	0.558		
Total	266.401	171			

The aggregate regression model for AI adoption intention exhibits almost the same explanatory power as the original variable model (Table 22). R is 0.804 and Adjusted R² is 0.642 which are both approximately 0.02 lower than the previous model. The Durbin-Watson statistic with a value of 1.993 indicates almost no evidence of autocorrelation. ANOVA indicates that the regression model is statistically significant with $p < 0.001$ (Table 23). Figures 15 to 17 exhibit similar diagnostic behavior as the previous model in terms of linearity, normality and heteroscedasticity, with no obvious indication of major deviations. Since the same dependent variable data are used here the diagonal patterns are present in the residual plot here too.

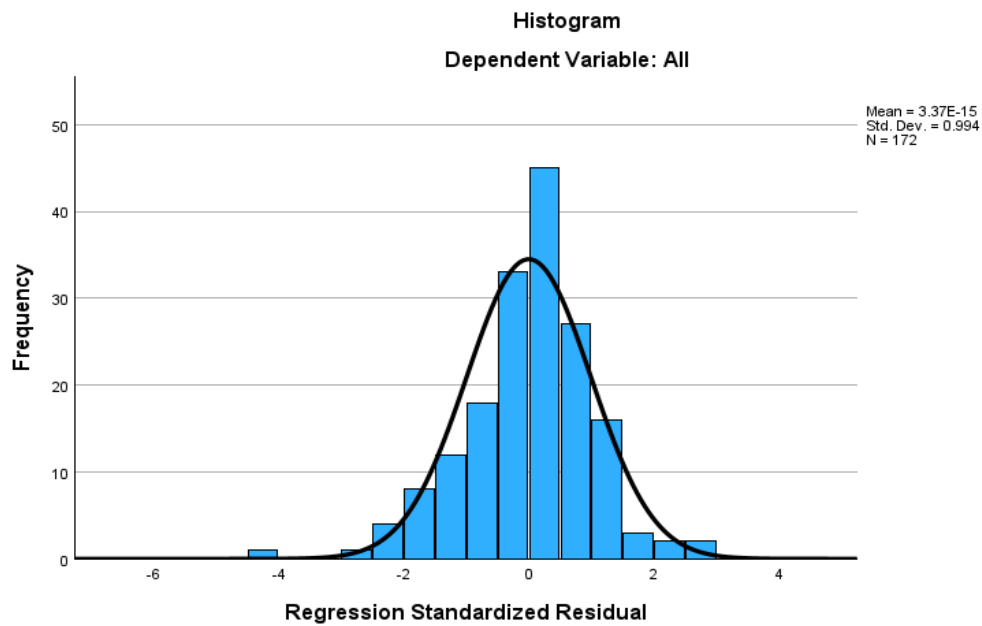


Figure 15. Histogram of Residuals for AI adoption intention for the aggregate construct regression case.

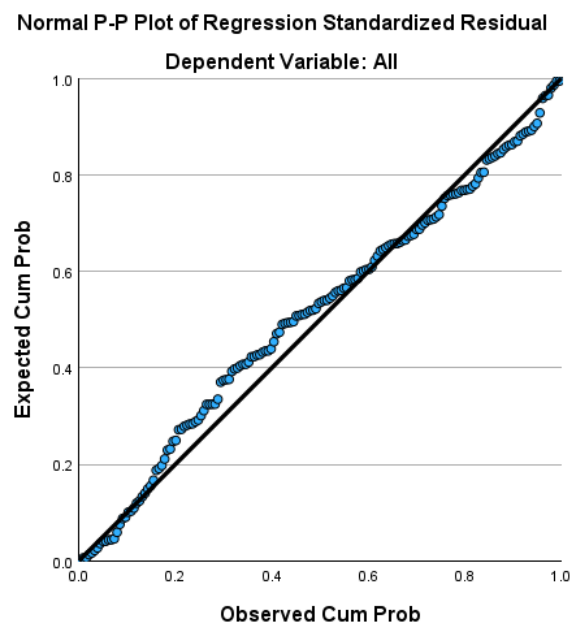


Figure 16. Normal P-P plot of residuals for AI adoption intention for the aggregate construct regression case.

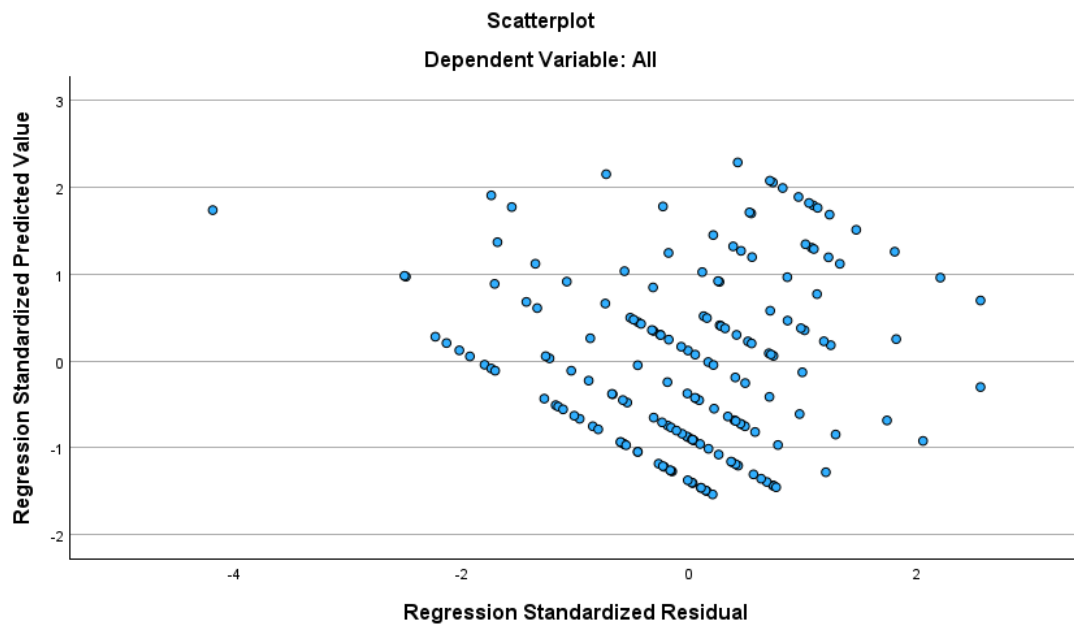


Figure 17. Residual Scatterplot for AI adoption intention for the aggregate construct regression case.

Table 24. Regression coefficients for AI adoption intention for the aggregate construct case.

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics
	B	Std. Error	Beta			VIF
(Constant)	0.493	0.388		1.270	0.206	
DigStateAndAIreadiness	0.915	0.070	0.741	13.029	0.000	1.544
COMPL	-0.113	0.065	-0.099	-1.735	0.085	1.544

In table 24 the aggregate model for AI adoption intention exhibits statistical significance of the Digital State and AI Readiness predictor at the 5% level, while the Complexity predictor is not statistically significant ($p=0.085$). The VIF values of 1.544 indicate low multicollinearity. The standardized beta of the statistically significant variable is large ($\beta=0.741$). Overall, the aggregate variable model behaves comparably to the original variable model, while being much simpler and due to low VIF exhibits substantially reduced multicollinearity concerns.

4.7 Summary of findings

The regression analysis with the original variable/construct set resulted in the hypothesis testing results reported in Table 25. There was statistical evidence to support the alternative

hypotheses and reject the null hypotheses for H3s, H3i, H4s, H4i and H5s which means that it is supported that Data Readiness and Compatibility positively affect AI adoption State and AI adoption intention while Complexity negatively affects AI adoption State. There was marginal significance for the impact of IT Knowledge on AI adoption state ($p=0.069$). For the hypotheses for the impact of Infrastructure on the variables and IT Knowledge and Complexity effect on AI adoption intention we did not have enough statistical evidence to reject the null hypotheses and thus the alternate hypotheses were not supported.

Table 25. Hypothesis testing results.

Hypothesis	Description	Result	Status
H _{1s}	Infrastructure positively affects AI adoption state	No statistical significance	Not Supported
H _{1i}	Infrastructure positively affects AI adoption intention	No statistical significance	Not Supported
H _{2s}	IT Knowledge positively affects AI adoption state	Marginal significance ($p=0.069$)	Partially Supported
H _{2i}	IT Knowledge positively affects AI adoption intention	No statistical significance	Not Supported
H _{3s}	Data Readiness positively affects AI adoption state	Positive significant effect	Supported
H _{3i}	Data Readiness positively affects AI adoption intention	Positive significant effect	Supported
H _{4s}	Compatibility positively affects AI adoption state	Positive significant effect	Supported
H _{4i}	Compatibility positively affects AI adoption intention	Positive significant effect	Supported
H _{5s}	Complexity negatively affects AI adoption state	Negative significant effect	Supported
H _{5i}	Complexity negatively affects AI adoption intention	No statistical significance	Not Supported

The aggregate regression models indicate that the Digital State and AI Readiness variable which combines Infrastructure, IT Knowledge, Data Readiness and Compatibility exhibits strong explanatory capability of AI adoption state and AI adoption intention. This result, when combined with the EFA results that suggested the existence of two closely related factors which may be interpreted as technological competence and Digital Utilization and AI readiness, may indicate that Greek SMEs perceive their broader Digital State and AI Readiness in a holistic and interrelated way.

5. Discussion and AI adoption proposal

5.1 A deeper outlook on the survey results

The survey examined factors that influence the adoption of Artificial intelligence in Greek Small and Medium Enterprises (SMEs). Anchored to the question of how the digital maturity influences the AI adoption in businesses, the survey used the technological aspect of TOE-DOI framework as a basis for this study. The framework was expanded by the Data Readiness construct which was proposed based on relevant literature where it is consistently identified as an important enabler.

The results suggest that AI is in a relatively early adoption stage in Greek SMEs, and most businesses utilize AI on an experimental or limited basis. This result agrees with the literature which suggests that most businesses have not integrated AI use in a consistent and complete way, but they are still testing it. Usage in most cases appears to revolve around use of GenAI tools that are easier to use at an introductory level. Basic automation, content creation and consulting-related support appear to be the most common uses (though the survey did not test the usage with such specificity). On the other hand, predictive analytics or AI-driven production are less common, which may be attributed to the higher specialization needed for their use.

Another literature result that the survey confirms is the difference in adoption relative to the business size. Larger businesses exhibit higher AI adoption state and AI adoption intention compared to smaller businesses, which can be attributed to lower resource levels and lack of the organizational structure and specialized IT sections.

5.2 The survey's results

EFA suggests the existence of three dimensions, instead of five distinct constructs. While the literature conceptually separates the constructs, empirical correlation data in the same publications do not support complete construct independence. Specifically for Infrastructure and IT Knowledge there are low to moderate overlaps reported (Lin and Lin, 2008; Almashawreh et al., 2024). For Compatibility and Complexity literature results are not consistent and range from insignificant correlation (Lin & Ho, 2011) to strong correlation (Badghish and Soomro, 2024). Since Data Readiness is an added construct there is limited

literature evidence whether it behaves as an independent dimension from the other constructs.

The EFA results imply a meaningful grouping among the items and suggest an interpretation for them. The items that correspond to the first factor are items which appear to be related to resource existence and availability. The second factor is associated with items that either indicate utilization of digital systems and resources or compatibility with AI. Items that appear to include in their meaning aspects of both resource existence and utilization exhibit cross-loadings on both factors, with DAT3, DAT4 and DAT5 being such items. The third factor most probably corresponds to Complexity which loads strongly on that. Loadings from Compatibility items also exist for the third factor, probably due to high Compatibility leading to a perception of reduced difficulty of AI.

The inferential analysis revealed some significant results about the relation between the technological context of SMEs and AI adoption. The analysis suggests that Infrastructure is at an average level in Greek SMEs. Nonetheless, Infrastructure, while theoretically important, does not significantly affect AI adoption. In the survey, while businesses with low levels of Infrastructure consistently exhibit low levels of AI adoption, businesses with high levels exhibit spread values of AI adoption, with a tendency to higher values (Appendix B, table 31). This may tentatively indicate that while a theoretical enabler, Infrastructure appears to act more as a passive prerequisite whose influence may be absorbed by other factors, therefore reducing its apparent direct influence.

IT Knowledge results imply a comparable case with Infrastructure. Its mean level is slightly below the midpoint of the scale, while its significance in the regression is marginal for the AI adoption state model and it is non-significant for the AI adoption intention model. This leads to comparable conclusions, suggesting that IT Knowledge may act more as an enabling condition than a directly differentiating factor. Nonetheless, compared to Infrastructure, IT Knowledge appears somewhat more directly associated with AI adoption state.

While TOE relevant literature which tests Infrastructure and IT Knowledge influence on AI adoption state and AI adoption intention is limited, Infrastructure and IT Knowledge are usually identified as having significant relation to technological adoption (Lin and Lin, 2008; Almashawreh et al., 2024). This contradicts the results of this survey which suggest

only a marginally significant relationship between IT Knowledge and AI adoption state at 5% significance level.

The mean levels of both Infrastructure and IT Knowledge that are close to the midpoint of the scale support a picture of non-trivial digital maturity across Greek SMEs. This can be related, besides general recognition of digital benefits for businesses, to two specific conditions present in Greece. The first is the availability of multiple subsidy programs for digital transformation of businesses, which are funded through EU or national funds. The second is the tax law obligation which requires full interconnection of POS, cashier systems and accounting systems with the tax authority myData platform. An empirical finding that supports this is that the business function that exhibited the highest mean in digitalization state was Finance and Accounting. Moreover, 87.21% of the respondents answered that they used accounting or invoicing digital tools (Appendix B, table 29). While the format of the survey was not targeted to test this, the results imply that this connection may be real.

Data Readiness is significant for all regression models. This result is backed by both the literature (Bérubé et al., 2021; Grünbichler, 2023; Zavodna et al., 2024; Sánchez et al., 2025) and theory since AI technologies in most cases require good data quality to function properly. The fact that Data Readiness from a theoretical standpoint requires both Infrastructure and IT Knowledge, combined with the factor analysis results, suggest that Data Readiness may incorporate part of Infrastructure and IT Knowledge, possibly justifying their reduced significance in the models.

An interesting observation which relates to the Data Readiness analysis is that most respondents indicated that they use LLMs/GenAI in the used AI tools item. The rate was 72.09% (Appendix B, table 30) and was much higher than any other AI tool. While GenAI tools require vast amounts of data to function, these data are sourced by the model developers and used during training. During use, the data requirement depending on the actual task may be quite low. This can be combined with the fact that the only business function where AI use exhibited higher mean was Marketing. Marketing is one of the easiest uses of LLMs, specifically digital advertising and communication. A non-expert can ask the LLM, what is the best format for an advertisement in social media relatively easily. Contrary to that, inventory optimization often relies on machine learning systems which require knowledge in setting them up but more importantly a fully digitized inventory system that is kept up-to-date. It can be hypothesized that keeping an up-to-date inventory system,

especially for micro businesses, is more difficult than installing the AI system, which is a one-off operation that can be supported by a specialized third party. Even though the survey was not structured to test it, the above result may tentatively support the literature findings that many businesses are in experimental or pilot AI adoption phase, mainly experimenting with GenAI and according to our research mainly applying this experimentation to the Marketing business function.

Compatibility exhibited the highest significance for all regression models. From a theoretical standpoint this result is justified since a business that is compatible with AI across technological, operational and organizational dimensions, including processes, systems and organizational culture should be able to adopt it, integrate it and benefit from it more easily. Beyond the theoretical standpoint, compatibility can also in part overlap with the competence factors. Compatibility with digital systems could reflect the existence of infrastructure and data resources, while the operational compatibility could overlap with digital system utilization across business function and data utilization. This is supported by the EFA analysis especially along the digital system and data utilization contexts. While for Compatibility limited literature relevant to AI adoption exists Badghish & Soomro (2024) report, in accordance to this research's results, that Compatibility has significant relation to AI adoption at the 5% level of significance.

Finally, Complexity appears as a statistically significant barrier for AI adoption state but not for intention. This implies that complexity influences more the actual attempt to increase AI adoption but not as much the perceived need for businesses to adopt AI. Badghish & Soomro (2024) report that Complexity's influence on AI adoption is not significant, partially agreeing with the results of the research.

In Conclusion the results suggest that the broader technological state, which for the needs of this dissertation is named Digital State and AI Readiness is strongly correlated with AI adoption state and intention, while it is implied that the resource utilization subdimensions are the most significant contributions. The results imply that Greek SMEs could better facilitate their AI transformation and most importantly utilize AI to add value by first addressing the gaps in their digital transformation. They could achieve that mainly by transforming their operations to achieve better data readiness and better utilization of their digital resources, while better digital knowledge availability either directly among the

employees, or through regular support from IT consultants. Such a transformation should potentially transform firms into AI compatible organizations and lead to adoption.

5.3 Theoretical Contributions

The present research contributes to empirical research on technological influences on AI adoption in a number of ways. The research is based on TOE-DOI framework for technological adoption and extends it by including Data Readiness. The results imply that Data Readiness significantly influences AI adoption, confirming that including it in the technological context of TOE-DOI is empirically justified. Moreover, the research challenges assumptions on construct independence suggesting a more holistic perception of the technological context in Greek SMEs. The first identified dimension appears aligned with the existence and availability of digital resources including knowledge and data. The second empirical dimension aligns with the utilization of data and digital systems and general compatibility with AI. The third dimension appears to correspond to Complexity. An important contribution is the result that indicates a higher importance of the utilization related factors in regression compared to the resource existence ones. Finally, barriers as expressed by complexity, appear to affect the AI adoption state but do not seem to significantly contribute to the AI adoption intention.

5.4 AI adoption proposal

AI adoption has the potential to create value and competitive advantage to businesses if adopted in a way that increases performance, achieves better efficiency, reduces costs or improves marketing results. Even though actual results are an ongoing debate and credible data on the long-term performance of AI-mature businesses are still relatively sparse, it is reasonable that a strategy that focuses on practical gains, using calculated steps, may help businesses and especially SMEs, which do not usually have the capabilities for full transformations.

Especially for SMEs, it may be beneficial to start with the prerequisites. For businesses that have not started their digital transformation or that are at a very early stage of digitalization, an AI-focused strategy may not be the most appropriate path. Contrary to that, a

digitalization strategy may be what will help the business achieve better value. The dissertation does not suggest that such businesses should not pursue AI but this target may need to follow the dependencies upon which AI builds. Therefore, a plan incorporating the acquisition of proper infrastructure may represent an important first step for such businesses. Recently there have been many subsidy programs for digitalization of businesses in Greece which cover either the full cost or a significant part of the cost of hardware and software systems (Ministry of Digital Governance, 2022). Moreover, internet connectivity is rapidly increasing in Greece, with the main urban centers having access to fiber-optic connections while rural areas connectivity is also continuously improving.

Acquiring adequate infrastructure resources is comparatively the easiest part of the digital transformation path. Acquiring the knowledge required to use and integrate digital systems and digitalizing business operations may prove more difficult, as the survey suggests. This is the reason why programs targeting digital training and implementation may prove more important. Recently, such programs have been implemented, like the Digiwest program implemented by the Region of Western Greece (Region of Western Greece, n.d.). Such programs aim to help businesses develop their digital strategy and integrate digital systems into their daily operations. The guidance these programs offer is particularly important because, as the survey has indicated, the utilization of digital resources lags behind their availability. Thus, the consulting provided may help create the digital processes in the business which advance their digital transformation. Furthermore, the digitalization effort should include proper data practices, which include structured data logging, consistent data storage and regular data updating, in accordance with the thesis results.

Businesses at an appropriate digital maturity level are likely to be more compatible with AI and more capable of integrating AI systems into their operations. Moreover, they may have higher probability of achieving value from AI adoption, though this is a tentative at best statement, requiring further research.

This dissertation uses specific suggestion examples as a starting point to arrive to a generalized thought process on gradually increasing AI utilization. The first example, backed by the survey data observations, is the use of GenAI on marketing and specifically for creating a digital marketing strategy. This application should be relatively easy to adopt for businesses with low to medium digital maturity. The fact that GenAI can guide the user through the process of proposing a successful digital strategy facilitates its use, requiring

minimal knowledge. This application may provide observable results, allowing businesses with minimal digital presence to improve their digital presence, which may increase both their credibility in the market and their sales.

The second proposal is based on successful operational digitalization. Businesses with heavy inventory needs could benefit from minimizing the time stock remains in inventory, but also from minimizing stockouts. A machine learning system or even a simple knowledge-based expert system may help such a business if it possesses the necessary data to discover and predict inventory and demand patterns. Thus, it may be able to increase inventory efficiency which can improve working capital efficiency and potentially increase sales.

The general conclusion that the survey data support is that rather than treating AI adoption as the main goal, businesses should integrate AI adoption within a broader digital transformation strategy. This strategy should at each step focus on achieving the greatest incremental value for the business, which may be acquiring and integrating specific software, digitizing inventory operations or use of GenAI to help with digital marketing strategy.

A final suggestion that could be very useful is the use of GenAI as a meta-functionality tool, as it was suggested in previous sections. GenAI can act as a consultant that not only implements but also guides the implementation. In practical terms, GenAI can, beyond being a content creation tool, provide expertise around the task at hand. The example of guiding the digital strategy formulation is typical, probably being the easiest method of using AI to add value to businesses. The opportunity is that GenAI can act as an entry-level consultant of various specialties, at minimal cost, providing SMEs with services that were previously unavailable to them due to high costs.

6 Conclusion and Future Research

6.1 Main Conclusions

This dissertation examined the state of digital transformation of Greek SMEs and the relationship between technological context and AI adoption. The TOE-DOI framework was used, with the addition of the non-traditional construct of Data Readiness, emphasizing the aspects of resource utilization. For the needs of the thesis a quantitative online survey was performed which resulted in 181 responses of which 172 were considered valid.

The results suggest that while Greek SMEs have started experimentation with AI and especially GenAI tools, systematic or fully integrated use is limited. AI appears more frequently used for Marketing purposes, while application for other functions lags. The digital maturity of businesses appears lower than the midpoint of the Likert scale, with Infrastructure and IT Knowledge around the midpoint but utilization and data organization at lower levels.

The EFA suggests that for the survey's sample Infrastructure, IT Knowledge, Compatibility and Data Readiness are not fully independent latent constructs but they exhibit correlations. It is hypothesized that Greek SMEs perceive the tangible and intangible resources, which are Infrastructure, IT Knowledge and the existence-related part of Data Readiness as one latent factor, while the utilization of resources for business purposes, the handling of data, and the readiness of the business for AI are perceived as a second latent factor. Complexity is perceived as an independent factor with some contribution from compatibility items, possibly the subdimension that is perceived as AI adoption easiness. The analysis suggests that the Digital State and AI Readiness may be perceived more holistically by Greek SMEs and not as purely orthogonal factors.

For each dependent variable AI adoption state and AI adoption intention, two regression models were developed. The first model used a theoretically derived construct and variable structure based on the literature review. The variables were Infrastructure, IT Knowledge, Data Readiness, Compatibility and Complexity. The second model used empirical aggregate variables, and based on the three-factor structure suggested by the EFA as well as the correlations between the variables, combined the four constructs into one named Digital State and AI Readiness leaving Complexity as the second variable.

The analysis indicates that for the Survey's sample for AI adoption state the hypothesis that Data Readiness and Compatibility have a positive statistical effect and Complexity has a negative statistical effect are supported, while marginal support exists for the positive effect of IT Knowledge. The aggregate Digital State and AI Readiness also exhibits a significant positive effect. This model has marginally lower explanatory power, while it exhibits lower multicollinearity among the variables.

The results for AI adoption intention are similar, with the exception that Complexity's negative statistical effect is not supported. Moreover, the statistical effect of IT Knowledge is clearly not supported for this variable.

These results imply that the technological context is important for AI adoption, supporting the research question which hypothesized that digital transformation is related to AI adoption. An important observation is the strong correlation of the digital system utilization and the data readiness dimensions with adoption, which suggests that possibly these dimensions more directly affect adoption compared to resource-existence dimensions. Such a conclusion is also supported by the literature and theoretical considerations.

6.2 Limitations

Theoretical limitations of the survey include the fact that only the technological context was tested within the TOE-DOI framework and the organizational and environmental contexts were not tested. Moreover, the survey was cross-sectional and as such while it can detect association, it cannot credibly track causal relationships that a repeated survey could have been able to assess.

Methodological limitations include operationalization ambiguity owing to the variation in construct operationalization in TOE-DOI literature, as well as the additional exploratory items that were introduced in the survey. Furthermore, since the survey aims to get a single answer from each business, the opinions of the specific individual may not accurately represent the whole organization, and this could be more problematic for larger companies. Additionally, due to the multi-distribution path format for the questionnaire the inverse problem may have appeared which may occasionally lead to a company being represented by more than one response. The sample consists of 172 valid responses and is acceptable but a higher number of responses would strengthen the statistical results. The non-

probability sample with convenience sampling characteristics poses the risk of bias. The online nature of the questionnaire for instance may introduce a bias towards more digitally mature businesses.

The analysis performed did not include mediation testing which for the specific research would have been meaningful since hints of mediative relationships exist. Moreover, the multicollinearity of the variables poses a problem for the regression analysis, complicating coefficient interpretation and possibly reducing significance.

Finally, the survey is targeted at Greek SMEs and the results should not be generalized without caution to other contexts.

6.3 Future Research

The results suggest various directions for future research. Further research could examine potential revision of the TOE-DOI structures based on this research. Extension of the results to other countries and comparative studies can help define whether the results are globally aligned, while sector-based research can study the sectoral behavior. Qualitative studies can help better understand the construct perception patterns and provide better conceptual separation and itemization. Moreover, longitudinal studies can be employed to better assess the existence of a causal relationship between the technological factors and AI adoption.

Regarding the EFA results, further research could verify whether the derived factors are indeed latent constructs for the Greek SME population or the results were influenced by sample size, biases or specific item usage. In combination with that, future research could develop items that more clearly distinguish between resource existence and resource utilization to support or reject the EFA findings. Moreover, since results suggest that Data Readiness has a statistical effect, a mediation analysis could be performed to understand if it exhibits a mediating relationship between traditional resources like Infrastructure and IT knowledge and AI adoption. Moreover, there are hints of resource existence and availability influencing digital system utilization and AI compatibility. Since this in turn appears to influence AI adoption a mediation study among these variables could provide useful theoretical insights. Furthermore, moderation analysis using the demographic items, or other literature-derived or exploratory items could be performed. Finally, on the item design of future research there could be a division among general IT knowledge and AI related

knowledge so that the marginal importance suggested by the results of this dissertation can be further tested.

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Appendix A: Questionnaire of the survey

Greek version

**Η υιοθέτηση της Τεχνητής Νοημοσύνης στις ελληνικές Μικρό-Μεσαίες Επιχειρήσεις
και οι τεχνολογικές εξαρτήσεις της σύμφωνα με το μοντέλο TOE-DOI**

Ερωτηματολόγιο

Η παρούσα έρευνα εξετάζει το επίπεδο ψηφιακού μετασχηματισμού και την υιοθέτηση τεχνητής νοημοσύνης (AI) από τις μικρές και μεσαίες επιχειρήσεις στην Ελλάδα. Διεξάγεται στο πλαίσιο διπλωματικής εργασίας του Βασιλείου Παναγιωτόπουλου (email: std168992.ac.eap@gmail.com) για το πρόγραμμα MBA του Ελληνικού Ανοικτού Πανεπιστημίου.

Η συμπλήρωση του ερωτηματολογίου διαρκεί περίπου **10 λεπτά**. Οι απαντήσεις σας είναι **απολύτως εμπιστευτικές και ανώνυμες** και θα χρησιμοποιηθούν αποκλειστικά για ερευνητικούς σκοπούς, σε συγκεντρωτική μορφή. Δεν συλλέγονται προσωπικά δεδομένα που μπορούν να ταυτοποιήσουν εσάς ή την επιχείρησή σας.

Η συμμετοχή σας είναι **εθελοντική**, και μπορείτε να διακόψετε οποτεδήποτε τη συμπλήρωση. Τα δεδομένα σας διατηρούνται και επεξεργάζονται σύμφωνα με τον Γενικό Κανονισμό Προστασίας Δεδομένων (ΕΕ 2016/679- GDPR) και την ισχύουσα εθνική νομοθεσία περί προστασίας προσωπικών δεδομένων.

Μετά την ολοκλήρωση της έρευνας τα συνολικά αποτελέσματα θα δημοσιοποιηθούν σε συγκεντρωτική μορφή.

Σας ευχαριστούμε θερμά για το χρόνο και τη συμβολή σας!

Υποδομές- Γνώσεις Πληροφορικής- Δεδομένα

Απαντήστε σε ποιο βαθμό συμφωνείτε με τις παρακάτω προτάσεις με 1= Διαφωνώ απόλυτα και 5 = Συμφωνώ απόλυτα:

1. Η επιχείρησή μου διαθέτει επαρκή υπολογιστική υποδομή για την υποστήριξη των λειτουργιών της.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

2. Η επιχείρησή μου διαθέτει επαρκή κεντρική υποδομή (cloud ή server) για ψηφιακά εργαλεία ή διαχείριση/αποθήκευση δεδομένων.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

3. Η σύνδεση της επιχείρησής μου με το internet επαρκεί για τις ανάγκες της.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

4. Στην επόμενη ερώτηση επιλέξτε τα ψηφιακά εργαλεία που χρησιμοποιεί η επιχείρησή σας.

- ☐ Εφαρμογές Λογιστικής/Τιμολόγησης
- ☐ Εργαλεία Διαχείρισης Πελατών (CRM)
- ☐ Εργαλεία Οικονομικής Διαχείρισης/Επιχειρηματικού Σχεδιασμού (ERP)
- ☐ Εργαλεία Διαχείρισης Ανθρώπινου Δυναμικού (HR)
- ☐ Εργαλεία Διαχείρισης Κοινωνικών Δικτύων (Social networks)
- ☐ Εργαλεία Εφοδιαστικής Αλυσίδας / Διαχείρισης Αποθήκης (supply chain/Inventory)
- ☐ Εξυπηρέτηση πελατών (chatbots, helpdesk)
- ☐ Εφαρμογές γραφείου (Office, κλπ.)
- ☐ Δεν έχουμε εφαρμόσει καμία
- ☐ Δεν γνωρίζω / Δεν απαντώ
- ☐ Άλλο (παρακαλώ προσδιορίστε).....

5. Οι επόμενες ερωτήσεις αποσκοπούν στο να μετρήσουν το επίπεδο ψηφιοποίησης της επιχείρησής σας. Επιλέξτε μεταξύ 1 = Καθόλου ψηφιοποιημένη λειτουργία μέχρι 5 = πλήρως ψηφιοποιημένη λειτουργία)

Λειτουργία	1	2	3	4	5
Κύρια δραστηριότητα (Παραγωγή ή Παροχή Υπηρεσιών)	☐	☐	☐	☐	☐
Προμήθειες και Διαχείριση αποθεμάτων/ logistics	☐	☐	☐	☐	☐
Οικονομική διαχείριση / λογιστήριο	☐	☐	☐	☐	☐

Λειτουργία	1	2	3	4	5
Πωλήσεις /e-shop/ παραγγελιοληψία	☐	☐	☐	☐	☐
Marketing / επικοινωνία	☐	☐	☐	☐	☐
Εξυπηρέτηση πελατών	☐	☐	☐	☐	☐
Αναφορές και ανάλυση δεδομένων για επιχειρηματικές αποφάσεις (π.χ. dashboards, reports)	☐	☐	☐	☐	☐

Απαντήστε σε ποιο βαθμό συμφωνείτε με τις παρακάτω προτάσεις με 1 = Διαφωνώ απόλυτα και 5 = Συμφωνώ απόλυτα:

6. Η επιχείρησή μου χρησιμοποιεί μετρήσεις από τα social media (π.χ. reach, engagement, clicks) για τη συστηματική προσαρμογή της στρατηγικής marketing της.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

7. Η επιχείρησή μου χρησιμοποιεί δεδομένα από ψηφιακά συστήματα (π.χ. CRM, ERP, e-shop) για προσωποποιημένες ενέργειες marketing ή επικοινωνίας προς πελάτες.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

8. Η επιχείρησή μου χρησιμοποιεί ψηφιακά συστήματα που εκτελούν αυτόματα απλές λειτουργίες (π.χ. ειδοποιήσεις, υπενθυμίσεις, αυτόματες ενημερώσεις).

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

9. Το προσωπικό της επιχείρησης διαθέτει τις απαραίτητες γνώσεις για να χρησιμοποιεί αποτελεσματικά τα ψηφιακά εργαλεία που διαθέτει η επιχείρηση.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

10. Η επιχείρηση διαθέτει την τεχνογνωσία (εσωτερικά ή μέσω συνεργατών) για να προσαρμόσει, να παραμετροποιήσει ή να εγκαταστήσει νέα ψηφιακά συστήματα όταν χρειάζεται.
- 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐
11. Η επιχείρησή μου έχει υλοποιήσει ή αναβαθμίσει ψηφιακά συστήματα (π.χ. ERP, CRM, e-shop, λογιστικό πρόγραμμα) τα τελευταία 5 έτη.
- 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐
12. Η επιχείρηση χρησιμοποιεί τα ψηφιακά συστήματα που διαθέτει για να συλλέξει και να αποθηκεύσει πληροφορίες σχετικά με την λειτουργία της (π.χ. πωλήσεις, αποθέματα, πελάτες).
- 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐
13. Η επιχείρησή μου καταγράφει συστηματικά ψηφιακά δεδομένα σχετικά με τη λειτουργία της (π.χ. πωλήσεις, πελάτες, αποθέματα).
- 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐
14. Η επιχείρηση έχει συγκεκριμένα πρότυπα με τα οποία αποθηκεύει τα δεδομένα της ώστε να είναι εύκολη η αναζήτηση σε αυτά και η ανάκτησή τους όταν χρειαστεί (π.χ. κοινή ονομασία αρχείων, τυποποιημένα πεδία, σταθερός τρόπος καταχώρησης).
- 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Συμβατότητα

Απαντήστε σε ποιο βαθμό συμφωνείτε με τις παρακάτω προτάσεις με 1= Διαφωνώ απόλυτα και 5 = Συμφωνώ απόλυτα:

15. Η ενσωμάτωση συστημάτων Τεχνητής Νοημοσύνης (AI) στα υφιστάμενα πληροφοριακά συστήματα της επιχείρησης είναι εύκολη.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

16. Τα συστήματα Τεχνητής Νοημοσύνης είναι συμβατά με τις υφιστάμενες διαδικασίες της επιχείρησής μου.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

17. Τα συστήματα Τεχνητής Νοημοσύνης είναι συμβατά με την οργανωσιακή κουλτούρα και τις αξίες της επιχείρησής μου.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Πολυπλοκότητα

Απαντήστε σε ποιο βαθμό συμφωνείτε με τις παρακάτω προτάσεις με 1= Διαφωνώ απόλυτα και 5 = Συμφωνώ απόλυτα:

18. Η κατανόηση των συστημάτων Τεχνητής Νοημοσύνης (AI) είναι δύσκολη για την επιχείρησή μου.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

19. Ο διαμοιρασμός γνώσης σχετικά με τα συστήματα Τεχνητής Νοημοσύνης (AI) προς και μεταξύ των εργαζομένων της επιχείρησής μου είναι δύσκολος για την επιχείρησή μου.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

20. Η αποτελεσματική χρήση συστημάτων Τεχνητής Νοημοσύνης απαιτεί εξειδικευμένη εμπειρία.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Επίπεδο Υιοθέτησης Τεχνητής Νοημοσύνης (AI)

Απαντήστε σε ποιο βαθμό συμφωνείτε με τις παρακάτω προτάσεις με 1= Διαφωνώ απόλυτα και 5 = Συμφωνώ απόλυτα:

21. Η επιχείρησή μου βρίσκεται σε προχωρημένο στάδιο υιοθέτησης της Τεχνητής Νοημοσύνης (AI).

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

22. Στην επιχείρησή μου χρησιμοποιούνται εργαλεία AI σε τακτική και επαναλαμβανόμενη βάση.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

23. Στην επιχείρησή μου χρησιμοποιούνται τα δεδομένα από τη διασύνδεση τιμολόγησης/ myData/ POS για ανάλυση/ προβλέψεις/ προτάσεις.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

24. Στις παρακάτω ερωτήσεις απαντήστε το βαθμό στον οποίο αξιοποιείτε την Τεχνητή Νοημοσύνη σε κάθε λειτουργία της επιχείρησής σας σε κλίμακα από 1 = Καθόλου έως 5 = Πλήρως.

Λειτουργία	1	2	3	4	5
Προμήθειες και προμηθευτές	☐	☐	☐	☐	☐
Παραγωγή / Παροχή Υπηρεσιών	☐	☐	☐	☐	☐
Έρευνα και Ανάπτυξη	☐	☐	☐	☐	☐
Διαχείριση αποθεμάτων/ logistics	☐	☐	☐	☐	☐
Οικονομική διαχείριση / λογιστήριο	☐	☐	☐	☐	☐
Πωλήσεις /e-shop/ παραγγελιοληψία	☐	☐	☐	☐	☐
Marketing / επικοινωνία	☐	☐	☐	☐	☐
Εξυπηρέτηση πελατών	☐	☐	☐	☐	☐
Διαχείριση ανθρώπινου δυναμικού (HR)	☐	☐	☐	☐	☐
Εσωτερική επικοινωνία/ συνεργατικά εργαλεία	☐	☐	☐	☐	☐
Αναφορές και ανάλυση δεδομένων για επιχειρηματικές αποφάσεις (π.χ. dashboards, reports)	☐	☐	☐	☐	☐

25. Κατά το τελευταίο έτος χρησιμοποιήσατε στην επιχείρησή σας κάποιο από τα παρακάτω εργαλεία ή πλατφόρμες AI;

- ☐ Εργαλεία συνομιλιακής (conversational) TN/ παραγωγής κειμένου (π.χ. ChatGPT, Gemini, Copilot, κ.α.)
- ☐ Εργαλεία δημιουργίας περιεχομένου με AI (π.χ. Canva, Notion, εικόνα/βίντεο/marketing)
- ☐ Συστήματα ανάλυσης δεδομένων και προβλέψεων (π.χ. πρόβλεψη πωλήσεων, ζήτησης, τάσεων)
- ☐ CRM/ERP με ενσωματωμένες λειτουργίες AI (π.χ. scoring πελατών, forecasting, recommendations)
- ☐ Συστήματα αυτοματοποίησης διαδικασιών με AI (π.χ. έξυπνα workflows, chatbots)
- ☐ Δεν χρησιμοποίησαμε
- ☐ Δεν γνωρίζω / Δεν απαντώ
- ☐ Άλλο (παρακαλώ προσδιορίστε).....

Πρόθεση υιοθέτησης Τεχνητής Νοημοσύνης

Απαντήστε σε ποιο βαθμό συμφωνείτε με τις παρακάτω προτάσεις με 1= Διαφωνώ απόλυτα και 5 = Συμφωνώ απόλυτα:

26. Η επιχείρησή μου σκοπεύει να υιοθετήσει ή να επεκτείνει τη χρήση εργαλείων AI μέσα στους επόμενους 12-24 μήνες.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

27. Η επιχείρησή μου διαθέτει συγκεκριμένο σχεδιασμό για την υιοθέτηση ή διερευνά λύσεις AI.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Δημογραφικά Στοιχεία

A.1 Ποιος είναι ο κλάδος βασικής δραστηριότητας της επιχείρησής σας;

- ☐ Μεταποίηση
- ☐ Εμπόριο
- ☐ Υπηρεσίες
- ☐ Τουρισμός
- ☐ Πληροφορική/Τεχνολογία
- ☐ Κατασκευές
- ☐ Αγροδιατροφή
- ☐ Logistics(εφοδιαστική)
- ☐ Άλλος (παρακαλώ προσδιορίστε)
- ☐ Δεν γνωρίζω/ Δεν απαντώ

A.2 Ποιος είναι ο αριθμός εργαζομένων στην επιχείρησή σας;

- ☐ 0-9
- ☐ 10-49
- ☐ 50-249
- ☐ >250
- ☐ Δεν γνωρίζω/ Δεν απαντώ

A.3 Ποιος είναι ο ετήσιος κύκλος εργασιών σας (τελευταία χρήση);

- ☐ <100.000€
- ☐ 100.000-499.999€
- ☐ 500.000-1,99 εκ. €
- ☐ 2-9,99 εκ. €
- ☐ 10-49,99 εκ. €
- ☐ >50 εκ. €
- ☐ Δεν γνωρίζω/ Δεν απαντώ

A.4 Σε ποια Περιφέρεια βρίσκεται η έδρα της επιχείρησής σας;

- ☐ Ανατολική Μακεδονία & Θράκη
- ☐ Κεντρική Μακεδονία

- ☐ Δυτική Μακεδονία
- ☐ Ήπειρος
- ☐ Θεσσαλία
- ☐ Ιόνια Νησιά
- ☐ Δυτική Ελλάδα
- ☐ Στερεά Ελλάδα
- ☐ Αττική
- ☐ Πελοπόννησος
- ☐ Βόρειο Αιγαίο
- ☐ Νότιο Αιγαίο
- ☐ Κρήτη
- ☐ Δεν γνωρίζω / Δεν απαντώ

A.5 Διαθέτει η επιχείρησή σας εξειδικευμένο προσωπικό IT (δηλαδή πληροφορικής) ή ψηφιακού μετασχηματισμού;

- ☐ Ναι, εσωτερική ομάδα
- ☐ Ναι, εξωτερικός συνεργάτης
- ☐ Και τα δυο
- ☐ Όχι
- ☐ Δεν γνωρίζω / Δεν απαντώ

A.6 Ποιος είναι ο ετήσιος προϋπολογισμός για τεχνολογίες πληροφορικής και επικοινωνιών (ΤΠΕ) (κατ' εκτίμηση);

- ☐
- ☐ Δεν γνωρίζω / Δεν απαντώ

A.7 Ποια είναι η θέση σας στην επιχείρηση;

- ☐ Ιδιοκτήτης/ Συνιδρυτής
- ☐ Διευθύνων / Γενικός Διευθυντής
- ☐ Μέλος Δ.Σ.
- ☐ Διευθυντής Λειτουργίας/ Παραγωγής
- ☐ Διευθυντής Οικονομικών (CFO)
- ☐ Υπεύθυνος IT/ Ψηφιακού Μετασχηματισμού

- ☐ Marketing/ Πωλήσεις
- ☐ HR / Διοικητικές Υπηρεσίες
- ☐ Στέλεχος/ Υπάλληλος
- ☐ Δεν γνωρίζω / Δεν απαντώ
- ☐ Άλλο (παρακαλώ προσδιορίστε)

English version

AI adoption in Greek Small and Medium Enterprises and its technological dependencies according to the TOE-DOI model

Questionnaire

This survey examines the digital transformation and AI adoption levels within Greek Small and Medium Enterprises. The survey is conducted as part of Vasileios Panagiotopoulos's dissertation for the MBA programme of the Hellenic Open University.

The questionnaire requires approximately **10 minutes** to complete. Your responses remain completely **confidential and anonymous** and will only be used for research purposes in aggregate form. No personal data that can identify you or your business are collected.

Your participation is voluntary and you can stop completing the questionnaire at any time. Your data are stored and processed in accordance with the General Data Protection Regulation (EU 2016/679- GDPR) and the national data protection legislation in place.

After the completion of the survey, the overall results will be published in aggregate form.

Thank you kindly for your time and contribution!

Infrastructure- ICT knowledge- Data

Please answer to what extent you agree with the following statements with 1 = Strongly disagree and 5 = Strongly agree:

1. My business has adequate ICT infrastructure to support its operations.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

2. My business has adequate central infrastructure (cloud or server) for digital tools or data management/ storage.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

3. My business's internet connection is sufficient for its needs.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

4. In the next question, please select the digital tools that your business uses.

- ☐ Accounting/Invoicing applications
- ☐ Customer Relationship Management tools (CRM)
- ☐ Financial Management/ Enterprise Planning tools (ERP)
- ☐ Human Resources Management tools (HR)
- ☐ Social networks Management tools
- ☐ Supply Chain/ Inventory tools
- ☐ Customer Service (chatbots, helpdesk)
- ☐ Office Applications (Office, etc.)
- ☐ We have not implemented any
- ☐ I do not know/ No answer
- ☐ Other (Please specify).....

5. The following questions aim to measure the level of digitalization of your business.

Choose between 1 = Not at all digitized function to 5 = fully digitized function.

Function	1	2	3	4	5
Main activity (Production or Service Provision)	☐	☐	☐	☐	☐
Procurement and inventory	☐	☐	☐	☐	☐
Financial management / accounting	☐	☐	☐	☐	☐
Sales /e-shop/ Order taking	☐	☐	☐	☐	☐
Marketing / communication	☐	☐	☐	☐	☐
Customer service	☐	☐	☐	☐	☐

Function	1	2	3	4	5
Reporting and data analysis for business decisions (e.g. dashboards, reports)	☐	☐	☐	☐	☐

Please answer to what extent you agree with the following statements with 1 = Strongly disagree and 5 = Strongly agree:

6. My business uses social media metrics (e.g. reach, engagement, clicks) to systematically adjust its marketing strategy.
1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

7. My business uses data from digital systems (e.g. CRM, ERP, e-shop) for personalized marketing or communication actions towards customers.
1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

8. My business uses digital systems that automatically perform simple functions (e.g. notifications, reminders, automatic updates).
1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

9. The company's staff has the necessary knowledge to effectively use the digital tools available to the company.
1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

10. The company has the expertise (internally or through partners) to adapt, configure or install new digital systems when needed.
1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

11. My business has implemented or upgraded digital systems (e.g. ERP, CRM, e-shop, accounting programme) in the last 5 years.
1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

12. The business uses its digital systems to collect and store information about its operations (e.g. sales, inventory, customers).

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

13. My business systematically records digital data about its operation (e.g. sales, customers, inventory).

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

14. The business has specific standards with which it stores its data so that it is easy to search and retrieve them when needed (e.g. common file names, standardized fields, consistent way of recording).

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Compatibility

Please answer to what extent you agree with the following statements with 1 = Strongly disagree and 5 = Strongly agree:

15. Integrating AI systems into a company's existing information systems is easy.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

16. AI systems are compatible with my business's existing processes.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

17. AI systems are compatible with my company's organizational culture and values.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Complexity

Please answer to what extent you agree with the following statements with 1 = Strongly disagree and 5 = Strongly agree:

18. Understanding AI systems is difficult for my business.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

19. Sharing knowledge about AI systems to and among company employees is difficult for my company.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

20. The effective use of AI systems requires specialized experience.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Artificial Intelligence (AI) adoption level

Please answer to what extent you agree with the following statements with 1 = Strongly disagree and 5 = Strongly agree:

21. My business is in an advanced stage of adopting AI.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

22. My business uses AI tools on a regular and recurring basis.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

23. My business uses data from the billing/ myDATA/ POS interface for analysis/ forecasts/ suggestions.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

24. In the following questions, please answer the extent to which you utilize AI in each function of your business on a scale from 1 = Not at all to 5 = Completely.

Function	1	2	3	4	5
Procurement and suppliers	☐	☐	☐	☐	☐
Production/ Service provision	☐	☐	☐	☐	☐

Function	1	2	3	4	5
Research and Development	☐	☐	☐	☐	☐
Inventory management/ logistics	☐	☐	☐	☐	☐
Financial management/ accounting	☐	☐	☐	☐	☐
Sales/ e-shop/ order taking	☐	☐	☐	☐	☐
Marketing/ communication	☐	☐	☐	☐	☐
Customer service	☐	☐	☐	☐	☐
Human resources management (HR)	☐	☐	☐	☐	☐
Internal communication/ collaborative tools	☐	☐	☐	☐	☐
Reporting and data analysis for business decisions (e.g. dashboards, reports)	☐	☐	☐	☐	☐

25. During the last year have you used any of the following AI tools or platforms in your business?

- ☐ Conversational AI/ text generation tools (e.g. ChatGPT, Gemini, Copilot, etc.)
- ☐ AI-powered content creation tools (e.g. Canva, Notion, image/ video/ marketing)
- ☐ Data analysis and forecasting systems (e.g. sales, demand, trend forecasting)
- ☐ CRM/ERP with integrated AI functions (e.g. customer scoring, forecasting, recommendations)
- ☐ AI-powered process automation systems (e.g. smart workflows, chatbots)
- ☐ We did not use
- ☐ Don't know/ No answer
- ☐ Other (Please specify).....

Intention to adopt AI

Please answer to what extent you agree with the following statements with 1 = Strongly disagree and 5 = Strongly agree:

26. My business plans to adopt or expand the use of AI tools within the next 12-24 months.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

27. My business has a specific plan for adopting or is exploring AI solutions.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Demographics

A.1 What is the main sector of activity of your business?

- ☐ Manufacturing
- ☐ Trade
- ☐ Services
- ☐ Tourism
- ☐ Information and Communication Technology
- ☐ Construction
- ☐ Agri-food
- ☐ Logistics
- ☐ Other (please specify)
- ☐ Don't know/ No answer

A.2 What is the number of employees in your business?

- ☐ 0-9
- ☐ 10-49
- ☐ 50-249
- ☐ >250
- ☐ Don't know/ No answer

A.3 What is your annual turnover?

- ☐ <100.000€
- ☐ 100.000-499.999€
- ☐ 500.000-1,99 m. €
- ☐ 2-9,99 m. €
- ☐ 10-49,99 m. €
- ☐ >50 m. €
- ☐ Don't know/ No answer

A.4 In which region is your business's headquarters?

- ☐ Eastern Macedonia and Thrace
- ☐ Central Macedonia
- ☐ Western Macedonia
- ☐ Epirus
- ☐ Thessaly
- ☐ Ionian Islands
- ☐ Western Greece
- ☐ Central Greece
- ☐ Attica
- ☐ Peloponnese
- ☐ Northern Aegean
- ☐ Southern Aegean
- ☐ Crete
- ☐ Don't know/ No answer

A.5 Does your business have specialized IT or digital transformation staff?

- ☐ Yes, internal team
- ☐ Yes, external partner
- ☐ Both of the above
- ☐ No
- ☐ Don't know/ No answer

A.6 What is the annual budget for ICT (approximately)?

- ☐
- ☐ Don't know/ No answer

A.7 What is your role in the company?

- ☐ Owner/ Co-founder
- ☐ Managing director/ General manager
- ☐ Member of the board
- ☐ Operations/ Production manager
- ☐ Chief Financial Officer (CFO)
- ☐ IT/ Digital transformation manager
- ☐ Marketing/ Sales
- ☐ HR / Administrative services
- ☐ Middle manager/ Employee
- ☐ Don't know/ No answer
- ☐ Other (please specify)

Appendix B: Additional statistical results

Table 26. Frequencies and percentages of yearly turnover in the survey's sample.

Yearly turnover	Frequency	Percent
<100.000€	61	35.5
100.000-499.999€	33	19.2
500.000-1,99 εκ. €	26	15.1
2-9,99 εκ. €	20	11.6
10-49.99 εκ. €	2	1.2
Do not know/ Do not answer	30	17.4
Total	172	100.0

Table 27. Frequencies and percentages of "Has the business IT or Digital Transformation personnel" in the survey's sample.

Existence of IT personnel	Frequency	Percent
Yes, in-house team	14	8.1
Yes, external consultant	51	29.7
Yes, both	21	12.2
No	84	48.8
Do not know/ Do not answer	2	1.2
Total	172	100.0

Table 28. Frequencies and Percentages of role in the business in the survey's sample

Role in the company	Frequency	Percent
Owner/ Co-founder	80	46.5
Middle manager/ Employee	65	37.8
Managing director/ General manager	11	6.4
Operations/ Production manager	6	3.5
Marketing/ Sales	3	1.7
HR / Administrative services	2	1.2
Member of the board	2	1.2
IT/ Digital transformation manager	2	1.2
Do not know/ Do not answer	1	0.6
Total	172	100.0

Table 29. Frequencies and Percentages of implemented software categories for the businesses in the survey's sample

Tool Category	Frequency	Percent
Accounting/Invoicing	150	87.21
CRM	68	39.53
ERP	41	23.84
HR Management	12	6.98
Social Network Management	66	38.37
Supply Chain/Inventory	32	18.60
Customer Support	23	13.37
Office applications	129	75.00

Tool Category	Frequency	Percent
None implemented	5	2.91
Respondent Base*	172	100.0

*Multiple responses were permitted. Percentages are calculated using the 172 respondents as the denominator and therefore do not sum up to 100%.

Table 30. Frequencies and Percentages of use of specific AI tool categories in the past year in the survey's sample

Tool Category	Frequency	Percent
Conversational AI (eg ChatGPT)	124	72.09
Content Creation AI (eg Canva)	55	31.98
Data Analysis and Forecasting	19	11.05
CRM/ERP with integrated AI	14	8.14
Process automation with AI	24	13.95
Did not use	43	25.00
Respondent base*	172	100.0

*Multiple responses were permitted. Percentages are calculated using the 172 respondents as the denominator and therefore do not sum up to 100%.

Table 31. Crosstabulation between Infrastructure and AI adoption state with binning according to rounded values.

INF_bin * AIS_bin Crosstabulation								
			AIS_bin					Total
			1.00	2.00	3.00	4.00	5.00	
INF_bin	1.00	Count	15	0	0	0	0	15
		% within INF_bin	100.0%	0.0%	0.0%	0.0%	0.0%	100.0%
		% within AIS_bin	17.6%	0.0%	0.0%	0.0%	0.0%	8.7%
	2.00	Count	36	12	0	0	0	48
		% within INF_bin	75.0%	25.0%	0.0%	0.0%	0.0%	100.0%
		% within AIS_bin	42.4%	25.5%	0.0%	0.0%	0.0%	27.9%
	3.00	Count	28	13	5	1	1	48
		% within INF_bin	58.3%	27.1%	10.4%	2.1%	2.1%	100.0%
		% within AIS_bin	32.9%	27.7%	21.7%	7.1%	33.3%	27.9%
	4.00	Count	5	19	10	6	0	40
		% within INF_bin	12.5%	47.5%	25.0%	15.0%	0.0%	100.0%
		% within AIS_bin	5.9%	40.4%	43.5%	42.9%	0.0%	23.3%
	5.00	Count	1	3	8	7	2	21
		% within INF_bin	4.8%	14.3%	38.1%	33.3%	9.5%	100.0%
		% within AIS_bin	1.2%	6.4%	34.8%	50.0%	66.7%	12.2%
Total		Count	85	47	23	14	3	172
		% within INF_bin	49.4%	27.3%	13.4%	8.1%	1.7%	100.0%
		% within AIS_bin	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Author's Statement:

I hereby declare that, in accordance with article 8 of Law 1599/1986 and article 2.4.6 par. 3 of Law 1256/1982, this thesis/dissertation is solely a product of personal work and does not infringe any intellectual property rights of third parties and is not the product of a partial or total plagiarism, and the sources used are strictly limited to the bibliographic references.