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Adoption of Electronic Tendering Applications by
Greek Companies: A Study Based on the Unified Theory of
Acceptance and Use of Technology (UTAUT)

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Patras, Greece, June 2024



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Acknowledgments

To my supervisor and to all the respondents who took part in this research.

Dedication

To my parents

Abstract

In the digital age, procurement processes are becoming increasingly efficient through electronic tendering (e-tendering) applications, enhancing operational efficiency, transparency, and regulatory compliance across various sectors. This dissertation investigates the factors influencing the adoption of electronic tendering applications by Greek companies, using the Unified Theory of Acceptance and Use of Technology (UTAUT) as the analytical framework.

Through a quantitative approach, structured questionnaires were distributed to professionals in the Greek private sector who are involved in procurement or manage digital procurement solutions. The study examined the key constructs of the UTAUT model, including performance expectancy, effort expectancy, social influence, and facilitating conditions, along with the effects of other variables such as age, gender, experience, and voluntariness of use.

The results indicate that performance expectancy and social influence significantly and positively affect the behavioral intention to use e-tendering applications, while effort expectancy does not have a significant impact. Facilitating conditions and behavioral intention were found to significantly influence use behavior. Additionally, age was found to affect the impact of performance expectancy and effort expectancy on behavioral intention. This dissertation enriches the literature on technology adoption by applying the UTAUT model in the Greek corporate environment. Practically, it provides suggestions for businesses to design more effective e-tendering adoption strategies. Overall, this study clarifies the landscape of electronic tendering application adoption in Greece and suggests ways to enhance their broader acceptance and effective use.

Keywords

Electronic Tendering Applications, Unified Theory of Acceptance and Use of Technology, UTAUT

Περίληψη

Στην ψηφιακή εποχή, οι διαδικασίες προμηθειών γίνονται όλο και πιο αποδοτικές μέσω εφαρμογών ηλεκτρονικών διαγωνισμών (electronic tendering applications), ενισχύοντας την επιχειρησιακή αποδοτικότητα, τη διαφάνεια και τη συμμόρφωση με τους κανονισμούς σε διάφορους κλάδους. Η παρούσα διατριβή διερευνά τους παράγοντες που επηρεάζουν την υιοθέτηση των εφαρμογών ηλεκτρονικών διαγωνισμών από τις ελληνικές επιχειρήσεις, χρησιμοποιώντας τη Θεωρία Ενιαίας Αποδοχής και Χρήσης Τεχνολογίας (UTAUT) ως το αναλυτικό πλαίσιο.

Μέσω μιας ποσοτικής προσέγγισης, διανεμήθηκαν δομημένα ερωτηματολόγια σε επαγγελματίες του ιδιωτικού τομέα στην Ελλάδα που ασχολούνται με προμήθειες ή διαχειρίζονται ψηφιακές λύσεις προμηθειών. Η μελέτη εξέτασε τους βασικούς παράγοντες του μοντέλου UTAUT, συμπεριλαμβανομένων της αναμενόμενης απόδοσης, της αναμενόμενης προσπάθειας, της κοινωνικής επιρροής και των συνθηκών διευκόλυνσης, καθώς και των επιδράσεων άλλων μεταβλητών όπως η ηλικία, το φύλο, η εμπειρία και η εθελοντικότητα στη χρήση.

Τα αποτελέσματα δείχνουν ότι η αναμενόμενη απόδοση και η κοινωνική επιρροή επηρεάζουν σημαντικά και θετικά την πρόθεση χρήσης των εφαρμογών ηλεκτρονικών διαγωνισμών, ενώ η αναμενόμενη προσπάθεια δεν έχει σημαντική επίδραση. Οι συνθήκες διευκόλυνσης και η πρόθεση συμπεριφοράς βρέθηκαν να επηρεάζουν σημαντικά τη συμπεριφορά χρήσης. Επιπλέον, η ηλικία εντοπίστηκε να επηρεάζει την επίδραση της αναμενόμενης απόδοσης και της αναμενόμενης προσπάθειας στην πρόθεση συμπεριφοράς. Η παρούσα διατριβή εμπλουτίζει τη βιβλιογραφία για την υιοθέτηση της τεχνολογίας με την εφαρμογή του μοντέλου UTAUT στο ελληνικό εταιρικό περιβάλλον. Πρακτικά, παρέχει προτάσεις για τις επιχειρήσεις να σχεδιάσουν πιο αποτελεσματικές στρατηγικές υιοθέτησης ηλεκτρονικών διαγωνισμών. Συνολικά, η παρούσα μελέτη αποσαφηνίζει το τοπίο υιοθέτησης των εφαρμογών ηλεκτρονικών διαγωνισμών στην Ελλάδα και προτείνει τρόπους για να ενισχυθεί η ευρύτερη αποδοχή και αποτελεσματική χρήση τους.

Λέξεις – Κλειδιά

Εφαρμογές Ηλεκτρονικών Διαγωνισμών, Ενοποιημένη Θεωρία Αποδοχής και Χρήσης της Τεχνολογίας, UTAUT

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List of Abbreviations & Acronyms

ACCI= Athens Chamber of Commerce & Industry

ANOVA= Analysis of Variance

BI= Behavioral Intention

C-TAM-TPB: Combined Technology Acceptance Model and Theory of Planned Behavior

DM= Demographics

EDI= Electronic Data Interchange

EE= Effort Expectancy

ERP= Enterprise Resource Planning

EU= European Union

EX= Experience

FC= Facilitating Conditions

GEMI= General Commercial Registry of Greece

IDT= Innovation Diffusion Theory

IT= Information Technology

MM= Motivational Model

MPCU= Model of PC Utilization

PE= Performance Expectancy

SCT= Social Cognitive Theory

SI= Social Influence

SMEs= Small and medium-sized enterprises

SPSS= Statistical Package for the Social Sciences

SRM= Supplier Relationship Management

TAM= Technology Acceptance Model

TPB= Theory of Planned Behavior

TRA= Theory of Reasoned Action

UB= Use Behavior

UTAUT= Unified Theory of Acceptance and Use of Technology

VU= Voluntariness of Use

Chapter 1: Introduction

1.1 Topic of interest and purpose of the study

In the contemporary landscape of global commerce, digital transformation is reshaping how businesses operate, driving efficiencies, and enhancing competitive advantages across industries. In Greece, amidst an economy recovering from prolonged financial instability, companies are increasingly turning to digital procurement solutions to enhance their operational efficiencies and competitive standing. Among these digital solutions, electronic tendering (e-tendering) applications stand out for their potential to streamline procurement processes, from initiating supplier engagement to finalizing contracts. These applications promise not only to simplify workflows but also to offer greater transparency and efficiency throughout the procurement cycle. By replacing traditional, paper-based tendering processes that are often cumbersome and opaque, e-tendering applications promise streamlined operations, reduced overhead costs, and minimized human errors. This shift is crucial for Greek companies as it aligns with broader governmental reforms aimed at digitalizing public services, a move expected to catalyze efficiency and reduce corruption through enhanced transparency.

The transition from manual to electronic tendering is driven by multiple incentives: the potential for cost reduction, the increase in process efficiency, the broadening of supplier competition, and compliance with evolving regulatory standards that demand greater accountability and transparency. Digital tendering systems offer an organized, scalable platform for businesses to manage procurement activities, thereby enabling better data management, real-time updates, and more strategic supplier engagement. Yet, the adoption and successful integration of these technologies into existing systems present notable challenges. The integration of e-tendering into existing procurement frameworks involves significant changes in organizational processes, culture, and technology infrastructure. In Greece, these challenges are magnified by the specific socio-economic conditions and the historical reliance on entrenched traditional practices in business dealings. As such, understanding the factors that influence the acceptance and effective use of e-tendering applications is crucial for facilitating their successful adoption.

This dissertation aims to research the factors driving the adoption of digital procurement solutions, with a particular focus on e-tendering applications within the Greek business

context. It seeks to understand the complexities and challenges faced by Greek companies in integrating digital technologies that are crucial for streamlining procurement activities. Utilizing the Unified Theory of Acceptance and Use of Technology (UTAUT), this research aims to provide a comprehensive analysis of how performance expectancy, effort expectancy and social influence affect companies' intentions to adopt and use e-tendering systems. Also, how facilitating conditions and behavioral intentions affect actual behavior. Accordingly, this research addresses the pivotal question: "What are the key factors influencing the adoption of e-tendering applications by Greek companies, and how do these factors interplay to shape the decision-making processes regarding their use?"

1.2 Research approach

Rooted in the Unified Theory of Acceptance and Use of Technology (UTAUT), the study hypothesizes that key constructs such as performance expectancy, effort expectancy, social influence, and facilitating conditions, significantly predict the intention to use and the actual usage of e-tendering applications among Greek companies.

To address the research question and test the proposed hypotheses, a quantitative research methodology will be employed, utilizing a structured questionnaire, and will involve procurement professionals and decision-makers from various Greek companies. By leveraging the UTAUT model, the study will closely examine the interplay of UTAUT constructs in molding the intentions and behaviors of Greek companies regarding e-tendering applications. Data analysis will involve statistical techniques, including descriptive statistics for data summarization and inferential statistics, particularly regression analysis, to examine the relationships between UTAUT constructs and the adoption behavior.

1.3 Significance of the study

Understanding the adoption of e-tendering applications is crucial for enhancing procurement efficiency and competitiveness in the Greek market. The conclusions drawn are expected to offer actionable insights and strategies to facilitate the successful implementation and use of e-tendering applications, thereby enhancing operational efficiencies, transparency, and competitiveness in the Greek market. For academia, this study extends the application of the

UTAUT model in a relatively unexplored context—e-tendering adoption in Greece—thereby adding to the body of knowledge in technology adoption research.

1.4 Main limitations

While this study aims to provide comprehensive insights into the adoption of e-tendering applications, there are inherent limitations. The main limitation of this study concerns the chosen method of collecting the primary data, which is via an online questionnaire. The reliance on self-reported data from questionnaires may introduce biases that could affect the validity of the findings. Participants are less likely to stay fully engaged and thus not giving accurate responses. Additionally, the non-probability sampling technique, while cost-effective, may not fully represent the population of Greek companies using e-tendering systems. Another limitation concerns the size of the sample which can greatly affect the accuracy of the results. A further limitation concerns the small number of prior studies regarding the implementation of the UTAUT on the adoption of digital procurement solutions.

1.5 Study outline

The dissertation is consisted of five chapters as follows:

The first chapter (ch.1) introduces the topic of interest, outlining the study's purpose and significance. It also describes the research approach, briefly discusses the main limitations, and provides an overview of the dissertation structure.

The second chapter (ch.2) consists of a literature review, which provides information on digital procurement solutions and e-tendering applications, details on the UTAUT framework, discusses various factors, and presents the research hypotheses.

The third chapter (ch.3) explains the research methodology employed in the study, including a detailed presentation of the research instrument and measures.

The fourth chapter (ch.4) presents the research results and offers an analysis of the findings.

The fifth chapter (ch.5) includes a discussion of the research findings, explores the implications and limitations of the study, and provides a conclusion along with suggestions for future research.

Chapter 2: Literature Review

2.1 Introduction

The digital transformation of procurement processes through digital procurement systems, such as electronic tendering (e-tendering) applications, represents a significant shift in how companies across the globe, including those in Greece, manage their purchasing activities. This literature review provides an overview of the existing knowledge surrounding e-tendering applications, their adoption, and the broader context of digital procurement systems. It frames the study within the spectrum of established theories of technology acceptance and adoption, particularly focusing on the Unified Theory of Acceptance and Use of Technology (UTAUT) as a theoretical lens for analyzing the factors influencing e-tendering adoption in the Greek business landscape.

Digital procurement, often termed e-procurement, encompasses the integration of digital technology into all aspects of the procurement process. This includes tasks like automated supplier selection, electronic bidding, issuing purchase orders, digital contract management, and online transaction processing. The evolution of e-procurement systems has been marked by a significant transformation from traditional, manual processes to sophisticated, integrated digital platforms that facilitate real-time, transparent, and efficient procurement activities. The evolution from traditional procurement methods to digital ones is not merely a change in technology but also a strategic realignment of procurement to be more aligned with global standards of efficiency, transparency, and compliance. It is noted that the global procurement software market size was valued at approximately \$6.7 billion in 2022 and is projected to reach \$15.14 billion by 2031, growing at a compound annual growth rate (CAGR) of 9.4% during the forecast period (Astute Analytica, 2023). This growth is driven by the increasing adoption of digital procurement solutions across various industries.

Digital procurement systems represent a transformative approach within the supply chain management landscape, leveraging technology to optimize and streamline procurement processes. These solutions encompass a broad array of tools and platforms that facilitate electronic purchasing, supply chain management, and the automation of related administrative tasks. The tools include electronic purchasing systems, ERP (Enterprise Resource Planning) functionalities, and cloud-based data analytics for managing supplier relationships and performance metrics (Parida, Oghazi, & Cedergren, 2016).

The core functions of e-procurement systems include, but not limited to, creating and distributing tender documents electronically; automating the electronic submission and evaluation of bids from suppliers; automating the creation, approval, and dispatch of purchase orders to suppliers; enabling centralized access to approved supplier catalogs for users to select and order products; streamlining the process from initial requisition to payment to ensure all transactions are accurately recorded and tracked; automating the capture and approval of invoices, including matching with purchase orders and receipt of goods; and providing tools to manage contracts electronically from negotiation through renewal, including performance monitoring and compliance tracking. One key component of digital procurement solutions is Electronic Data Interchange (EDI), which facilitates the structured transmission of data between organizations electronically. EDI is one of the earliest forms of digital procurement technologies that enable the computer-to-computer exchange of documents such as purchase orders, invoices, and shipping notices, significantly speeding up transaction times and reducing errors (Fiala, 2005). E-Procurement software streamlines procurement activities by providing digital platforms where procurement requests can be placed, processed, and tracked. These systems often include features for online bidding and reverse auctions, which help secure the best prices by fostering competition among suppliers (Gunasekaran & Ngai, 2008). Supplier Relationship Management (SRM) systems are designed to automate and improve the relationships between a company and its suppliers. By using these systems, companies can manage supplier interactions more effectively, assess supplier risks, and optimize procurement strategy based on comprehensive analytics (Rossetti & Choi, 2005). Cloud-Based Procurement Solutions facilitate greater flexibility and scalability, allowing real-time data access and collaboration across different geographical locations while reducing the costs associated with maintaining IT infrastructure (Schniederjans & Hales, 2016). With the rise of mobile technology, procurement processes have also become increasingly mobile-friendly. Apps and mobile-optimized websites enable procurement officers to manage procurement tasks on the go, enhancing the responsiveness and agility of the procurement function (Kim & Shunk, 2004).

The shift towards digital procurement solutions, including e-tendering applications, offers several advantages that help organizations achieve their strategic objectives. Several studies highlight the benefits of digital procurement systems. Schniederjans and Hales (2016) indicate that digital procurement solutions significantly reduce procurement cycle times,

lower transaction costs, reducing overhead costs associated with manual processes and enhance the strategic alignment of procurement with overall business objectives. For instance, BCG's research indicated that digital solutions could reduce the end-to-end procurement process time by as much as 80% for simple items and 40% for complex items, highlighting the efficiency gains and time savings achieved through digital transformation in procurement (Biltoft-Knudsen et al., 2018). The implementation of digital procurement tools has been shown to enhance efficiency and improve supplier collaboration. Digital tools automate manual tasks, streamline workflows, minimizing human errors, leading to significant process efficiency improvements and translating these into direct cost savings (Rajkumar, 2001). Bain & Company reported that automating purchasing processes not only frees up resources for high value tasks like supplier negotiation and contract management, but also enhances strategic sourcing and supplier collaboration (Presutti, 2003; Radell & Schannon, 2018). Moreover, digital procurement aligns procurement functions with broader business objectives by enabling procurement teams to engage in more strategic activities such as agile partnerships and innovation. This strategic shift allows procurement to play a crucial role in accelerating business innovation and supporting company-wide goals (Radell & Schannon, 2018; Digital Adoption, 2023). Additionally, these systems improve data visibility, aiding better decision-making and compliance tracking (Hawking et al., 2004). Digital systems create an audit trail for all transactions, which is crucial for compliance and monitoring. Transparency in procurement processes helps prevent fraud and ensures adherence to policies and external regulations (Hawking et al., 2004). Advanced data analytics and real-time insights provided by digital procurement systems enable organizations to analyze spending patterns, supplier performance, market trends, support informed decision-making, risk management and strategic alignment, thereby driving business growth and maintaining competitiveness (Hawking et al., 2004). E-procurement also increases market access, allowing companies to engage with a broader network of suppliers, thus fostering stronger, more collaborative relationships. This can lead to improved service levels, more favorable terms, and innovations driven by closer supplier partnerships (Gunasekaran & Ngai, 2008; Croom & Brandon-Jones, 2007). For Greek companies, also this means access to a wider international market, enhancing competitive supply chains and potentially lowering procurement costs through increased supplier competition.

However, despite these advantages, the adoption of digital procurement solutions, including the e-tendering applications, faces several challenges. Cultural resistance, technological readiness, and the quality of the IT infrastructure are frequently cited as major impediments (Kurnia et al., 2015). Organizational inertia and resistance to change are common in companies with long-standing traditional processes. For instance, organizations with a strong reliance on traditional procurement methods may resist transitioning to digital systems due to perceived complexities and uncertainties. Employees used to traditional methods may resist adopting new technologies due to a lack of familiarity or fear of obsolescence (Patterson, Grimm, & Corsi, 2003). Furthermore, the specific features of e-tendering applications, such as their ability to support complex bidding processes and integrate with existing procurement software, are critical factors influencing their adoption (Zheng et al., 2008). The shift to e-tendering requires changes not only in technology but also in culture and business processes, which can meet considerable internal resistance (Patterson, Grimm, & Corsi, 2003). Integrating new digital procurement tools with existing IT systems can be complex, especially for organizations with outdated infrastructure. Also, the technical expertise needed not only for set-up of the systems but also for the ongoing maintenance and support may be lacking in many companies, especially Greek companies and SMEs (Small and Medium Enterprises). Ensuring compatibility and seamless data flow between different systems is critical but often challenging (Subramaniam & Shaw, 2002). Data breaches and cybersecurity threats are a significant concern with any digital system. Companies must ensure that their e-tendering applications are secure to protect sensitive commercial information. This requires additional investments in robust cybersecurity measures to protect sensitive information from unauthorized access and cyber threats, which can be a barrier for smaller businesses (Bélanger & Carter, 2008). In Greece, rapid changes in regulatory frameworks, particularly concerning digital transactions and data protection, can pose challenges to the deployment of e-tendering applications. Companies must continuously adapt their systems to comply with new regulations, which can be both costly and complex (Vassilakis et al., 2016). Last but not least, while digital procurement solutions can reduce costs in the long term, the initial investment in technology and training can be substantial. Small and medium-sized enterprises (SMEs) in particular may find the cost barrier significant (Gunasekaran & Ngai, 2008). Moreover, ensuring that staff are adequately trained to use these systems effectively is essential for successful implementation and adoption. Note, that training and educating staff can incur additional costs and time (Vaidya et al., 2006).

In summary, digital procurement solutions are reshaping the way organizations manage their procurement activities. As these solutions evolve, they continue to offer significant opportunities for enhancing operational efficiencies, improving supplier relationships, and achieving better compliance and transparency. However, realizing these benefits requires addressing the technological, organizational, and strategic challenges associated with digital transformation in procurement. By leveraging the insights provided by frameworks like UTAUT and addressing barriers to adoption, organizations can navigate the complexities of digital procurement and harness its full potential to drive business success.

2.2 E-Tendering Applications

E-tendering applications are at the forefront of digital procurement technologies. E-tendering, a critical subset of e-procurement, specifically refers to the use of digital platforms to manage the tendering process. This involves the electronic solicitation, submission, and evaluation of bids from suppliers. E-tendering applications streamline and standardize the tendering process, making it more efficient and transparent for all parties involved. The primary functions of e-tendering applications include creating and distributing tender documents electronically. These applications allow procurement teams to draft detailed tender specifications and distribute them to a wide network of suppliers with ease. This digital distribution ensures that all potential suppliers have equal access to tender opportunities, fostering a competitive bidding environment. Once bids are submitted, e-tendering applications facilitate the management and evaluation of these responses. The applications often include tools for automated bid evaluation based on customizable criteria and scoring mechanisms. This ensures that the evaluation process is objective, consistent, and transparent. By standardizing bid evaluation, e-tendering systems help in identifying the most suitable suppliers based on quality, cost, compliance, and other relevant factors. E-tendering applications also enhance communication and collaboration between buyers and suppliers. Features such as real-time messaging, document sharing, and query management ensure that all parties are well-informed throughout the tendering process. This improved communication reduces misunderstandings and accelerates decision-making. Moreover, e-tendering applications provide comprehensive audit trails and reporting capabilities. Every action taken within the system is logged, ensuring full traceability and accountability. These audit trails are crucial for compliance with regulatory requirements and for internal audits.

Traditionally, tendering processes were conducted manually, involving extensive paperwork, in-person negotiations, and a linear, often opaque sequence of operations. Literature identifies multiple dimensions of e-tendering benefits, including enhanced competitive advantage, increased procedural efficiency, and heightened transparency, which are essential for anti-corruption measures in both public and private sectors. The inception of e-tendering applications can be traced back to the late 1990s and early 2000s when businesses began to exploit the burgeoning capabilities of the Internet to enhance their operational efficiencies. Initially, these applications were simple, providing basic tools for online bid submission and management. Over time, as technology advanced, these applications have grown more sophisticated, incorporating complex data analytics, real-time communication, and integration with other business management software (Gunasekaran & Ngai, 2008). Today, it involves the use of advanced technologies such as blockchain, artificial intelligence and machine learning (Deloitte, 2017; MIT Technology Review, 2023). This transition was part of a broader digitalization trend that aimed to reduce costs, enhance speed, and improve the accuracy of data in procurement (Vaidya et al., 2006). In recent years, the proliferation of cloud computing, data analytics, and more advanced cybersecurity measures has further enhanced the capabilities and appeal of e-tendering applications. These technologies have enabled more robust, scalable, and secure platforms, encouraging their adoption across various industries (Neupane et al., 2014). Cloud computing has allowed e-tendering applications to become more scalable and accessible, enabling businesses of all sizes to implement these solutions without significant upfront investments in IT infrastructure (Schniederjans & Hales, 2016). Enhanced security protocols and tools have made e-tendering applications more robust against threats, addressing one of the primary concerns of online procurement processes (Bélanger & Carter, 2008). With the widespread use of smartphones and tablets, mobile-accessible e-tendering applications have increased the flexibility and immediacy with which procurement professionals can manage tenders (Kim & Shunk, 2004). Many e-tendering applications are now fully integrated with Enterprise Resource Planning (ERP) systems, allowing for seamless data flow and improved visibility across all procurement activities. The use of algorithms to automate the evaluation of bids based on pre-defined criteria (e.g., economical) is becoming more common, which helps reduce biases and improve the efficiency of the selection process (Gunasekaran & Ngai, 2008). There is an increasing emphasis on ensuring that procurement practices through e-tendering adhere to regulatory requirements and sustainability goals, which is pushing the development of features that can evaluate suppliers not just on cost, but on

compliance with diverse standards (Martins et al., 2014). This is particularly crucial in the European Union, where regulations are stringent and heavily enforced.

For Greek businesses, the adoption of e-tendering applications is influenced by both global trends and local economic conditions. The financial crisis of the past decade and the later Covid-19 pandemic had a profound impact on how Greek companies invest in and adopt new technologies, with many seeing digital transformation as a way to achieve greater financial control and operational efficiency (Vassilakis et al., 2016). The competitive pressures within and outside Greece encourage companies to adopt systems that can provide a competitive edge. The Greek government's push towards digitalization of public sector procurement to enhance transparency and reduce bureaucracy mandates similar changes in the private sector, particularly for companies engaged in public contracts. However, the economic instability experienced over the past decade has affected organizational readiness and willingness to adopt new technologies. Studies focusing on technology adoption in high uncertainty contexts suggest that external pressures, such as economic or regulatory changes, can significantly influence organizational behavior towards technology adoption (Vassilakis et al., 2016).

Overall, the transition from traditional to electronic tendering applications represents a significant evolution in procurement practices. The integration of advanced technologies such as cloud computing, mobile technology, and data analytics into e-tendering applications has created more efficient, transparent, and strategic procurement processes. As Greek businesses continue to navigate the challenges and opportunities presented by digital transformation, the adoption of e-tendering applications will likely continue to grow, driven by the need for greater efficiency, compliance, and competitive advantage.

The future of digital procurement and e-tendering applications is expected to involve a greater use of artificial intelligence and automation, enhanced integration with various business functions, and an increased emphasis on sustainability and ethical sourcing. As technology advances, procurement operations will need to continuously evolve to remain competitive and efficient in a swiftly changing global market.

Nowadays, there are various systems used by businesses and government organizations to streamline their procurement processes, improve transparency, and achieve cost savings. Some of the most prominent electronic procurement systems and e-tendering applications are listed below. These systems are designed to facilitate efficient and transparent

procurement processes, ensuring compliance and improving supplier relationships across various industries and sectors.

SAP Ariba: SAP Ariba is a comprehensive e-procurement platform that integrates sourcing, contract management, supplier collaboration, and spend analysis into a single cloud-based solution (figure 1). It connects buyers and suppliers globally, facilitating efficient transactions and providing real-time visibility into procurement activities. SAP Ariba includes tools for strategic sourcing and supplier management, streamlining procurement processes and enhancing supplier relationships. Its e-tendering application enables the creation, distribution, and management of tenders, supporting bid evaluation with customizable criteria and automated scoring, ensuring transparency and compliance (SAP, 2024).

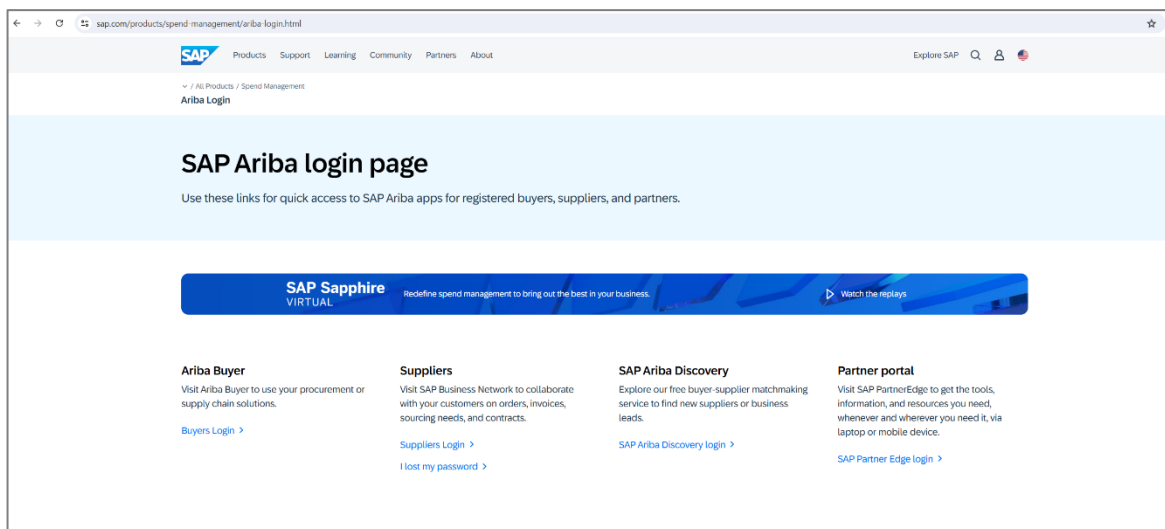


Figure 1. SAP Ariba webpage (SAP, 2024)

Oracle Procurement Cloud: Oracle Procurement Cloud is a robust e-procurement solution offering a comprehensive suite of tools for sourcing, procurement contracts, supplier qualification, and procurement operations (figure 2). Designed to enhance efficiency, ensure compliance, and reduce costs, the platform integrates seamlessly with Oracle's broader cloud ecosystem. Its user-friendly interface and advanced analytics help organizations make informed purchasing decisions. Oracle's e-tendering capabilities streamline bid solicitation and management, supporting electronic RFPs and ITTs, automated bid evaluation, and contract management (Oracle, 2024).

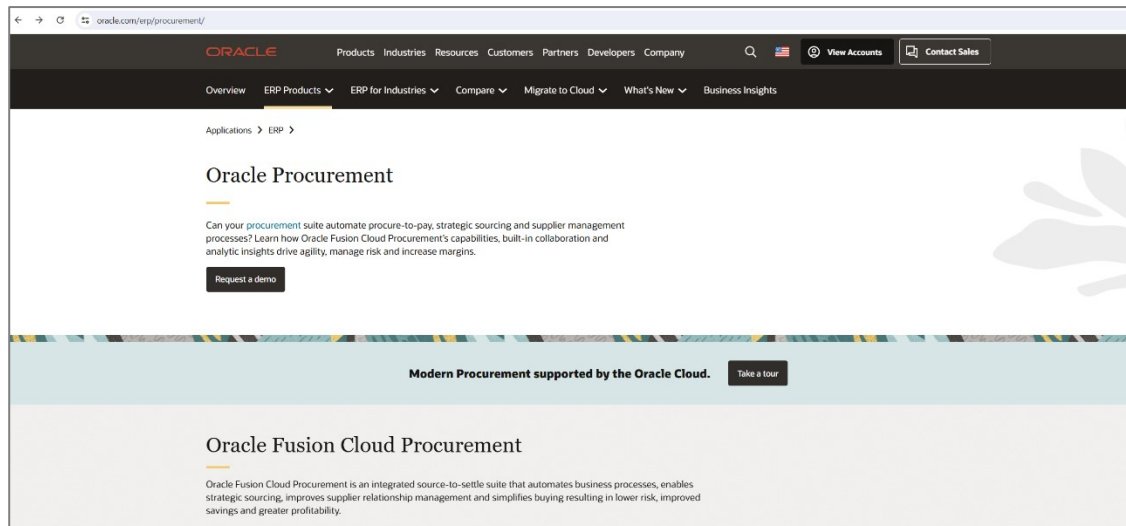


Figure 2. Oracle Procurement webpage (Oracle, 2024)

Coupa: Coupa is a cloud-based platform for spend management, encompassing procurement, invoicing, and expense management (figure 3). It simplifies and automates procurement processes, offering real-time visibility into spending and helping businesses control costs. Coupa's intuitive interface and robust analytics tools identify savings opportunities and improve financial performance. The platform's e-tendering solution manages tenders from creation to evaluation, using a centralized system for bid solicitation, response management, and automated scoring, ensuring transparent and compliant procurement (Coupa, 2024).

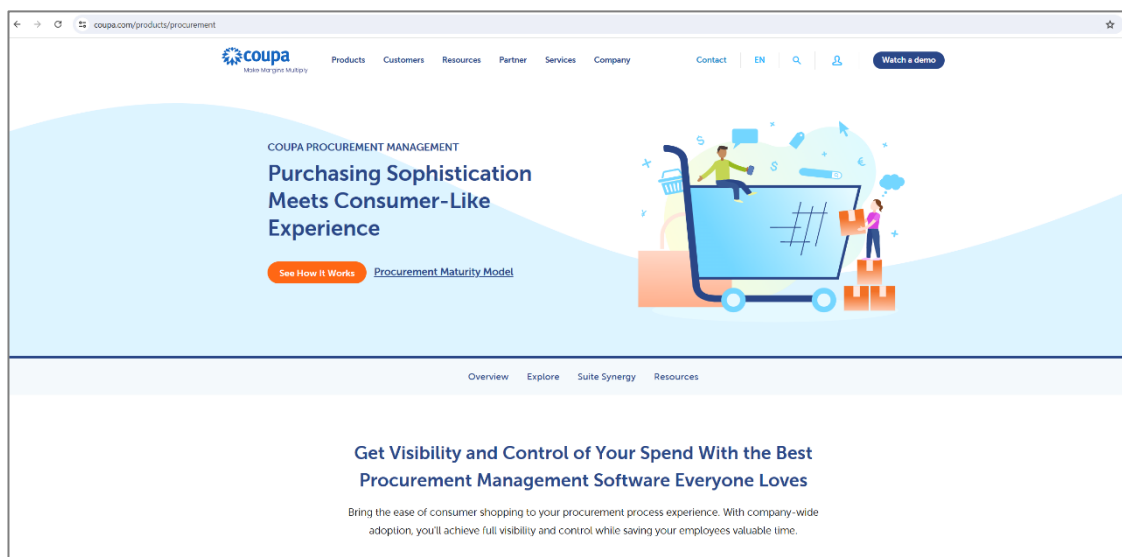


Figure 3. Coupa webpage (Coupa, 2024)

Jaggaer: Jaggaer provides a comprehensive suite of procurement solutions, including spend analytics, supplier management, e-sourcing, and contract management (figure 4). Known for its flexibility and scalability, Jaggaer serves various industries, offering tailored solutions to optimize procurement processes and manage supplier relationships. Its e-tendering application manages the entire tendering process digitally, featuring automated scoring and comparative analysis to aid bid evaluation. Integration with contract management tools ensures a seamless transition from tendering to contract execution (Jaggaer, 2024).

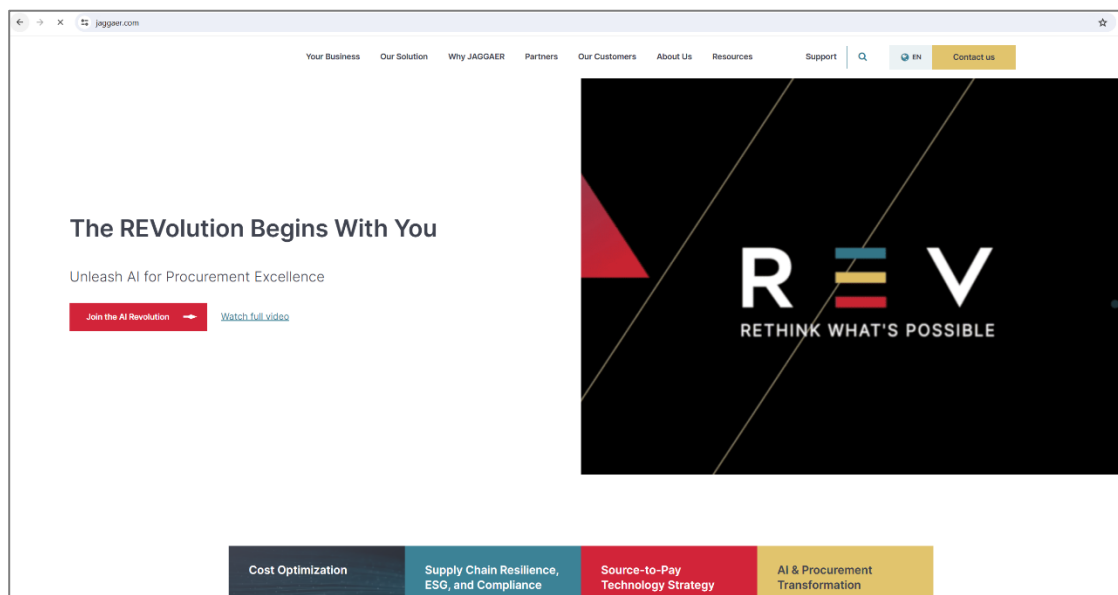


Figure 4. Jaggaer webpage (Jaggaer, 2024)

GEP SMART: GEP SMART is a unified procurement platform that includes modules for sourcing, contract management, supplier management, and procurement operations (figure 5). Leveraging AI and machine learning, it enhances procurement processes by providing actionable insights and automating tasks. GEP SMART's e-tendering capabilities streamline tender management, from drafting documents to evaluating bids with automated scoring. It supports electronic negotiations and integrates with other modules for a comprehensive procurement solution (GEP, 2024).

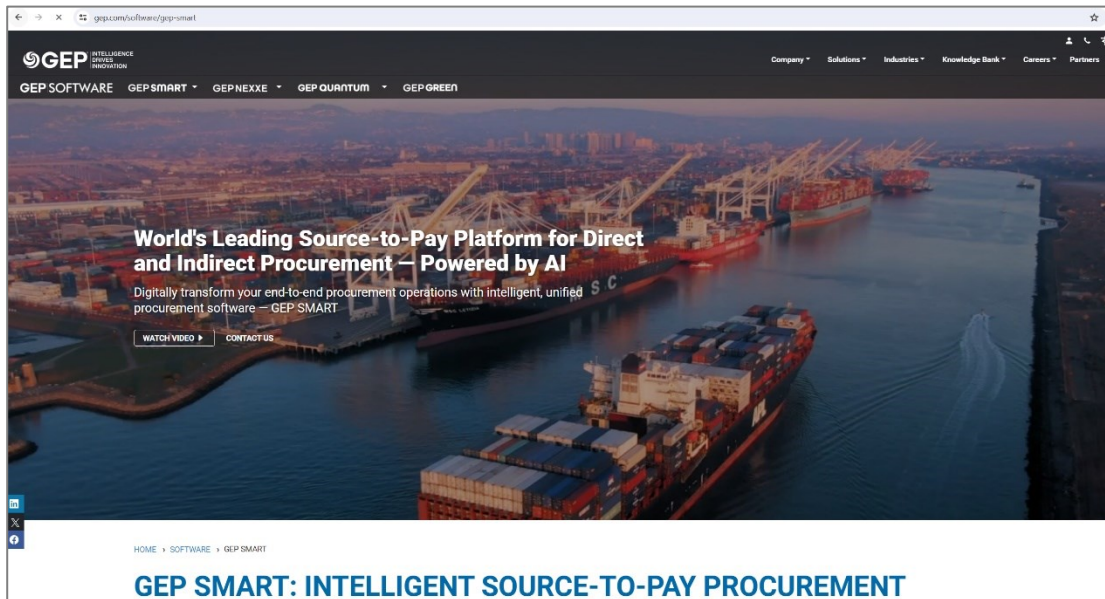


Figure 5. GEP SMART webpage (GEP SMART, 2024)

Ivalua: Ivalua offers an end-to-end procurement platform covering the entire procurement lifecycle, from sourcing to supplier management and analytics (figure 6). It provides full visibility into procurement activities, enabling data-driven decisions. Ivalua's modular design allows organizations to scale their capabilities as needed. The platform's e-tendering module supports electronic tender management, including tender creation, bid solicitation, and automated evaluation. Collaborative features ensure a thorough and transparent bid evaluation and supplier negotiation process (Ivalua, 2024).

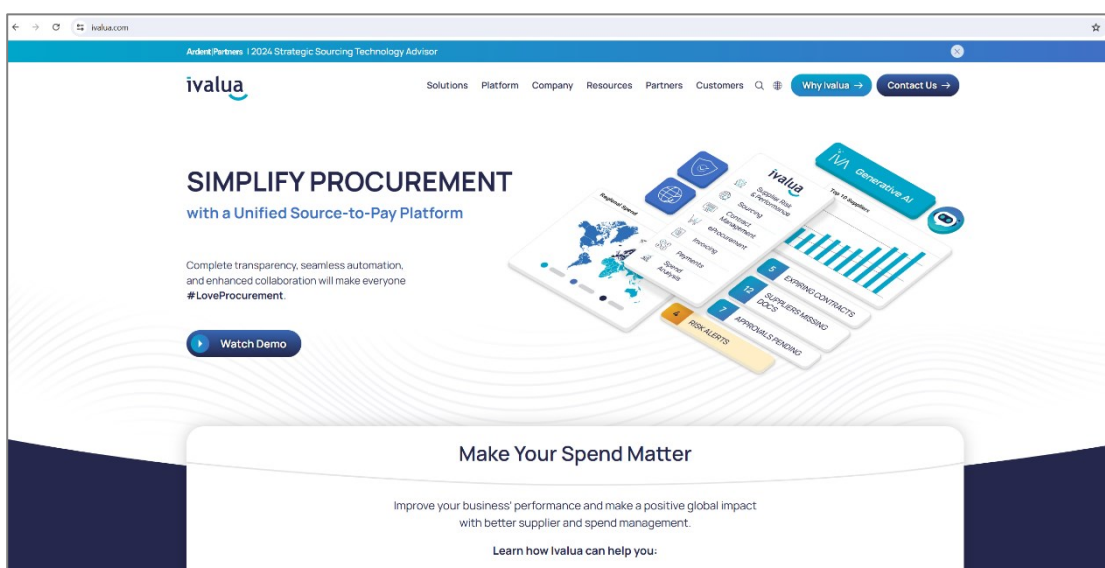


Figure 6. Ivalua webpage (Ivalua, 2024)

Proactis: Proactis offers procurement, spend management, and supplier engagement solutions (figure 7). Its platform streamlines procurement processes, enhances financial control, and improves supplier relationships. Proactis includes tools for e-sourcing, contract management, supplier management, and analytics. Its e-tendering application manages tender creation, bid submissions, and evaluations through a centralized portal, with automated scoring to ensure fair supplier selection. The platform also supports contract management and compliance monitoring (Proactis, 2024).

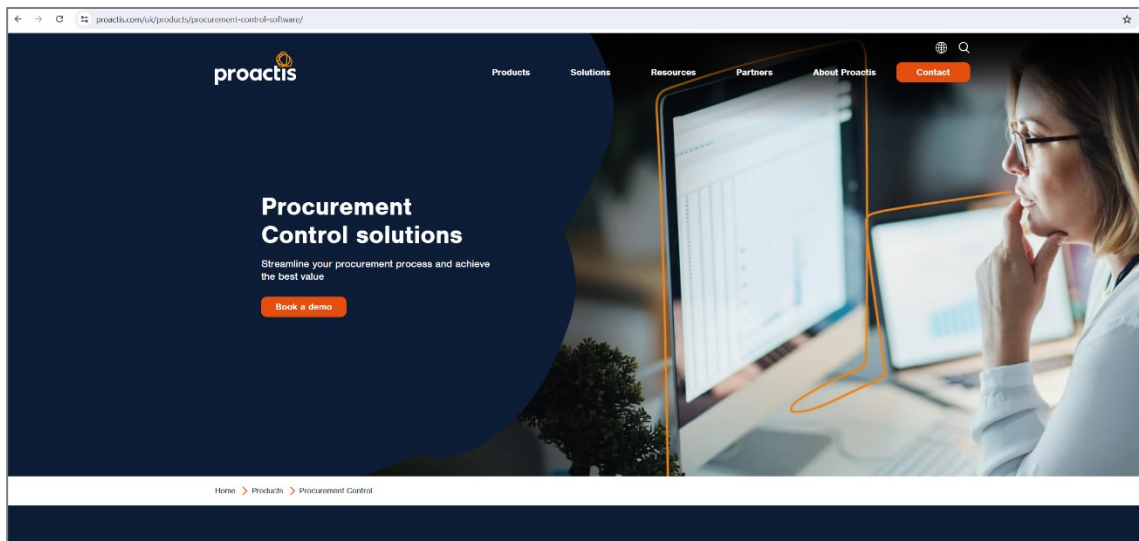


Figure 7. Proactis webpage (Proactis, 2024)

SynerTrade: SynerTrade provides a complete suite of procurement applications, including sourcing, supplier management, and analytics (figure 8).

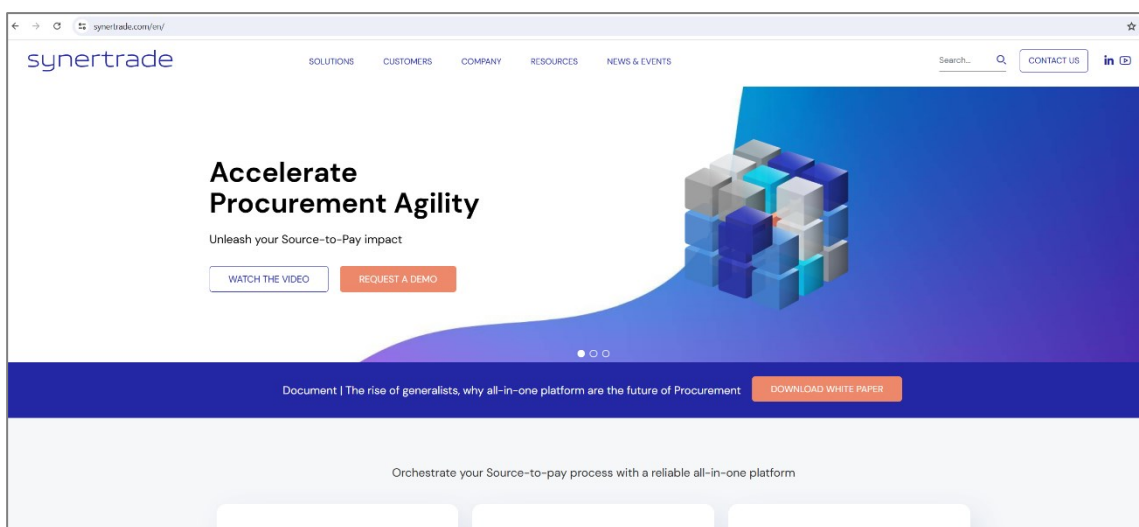


Figure 8. SynerTrade webpage (SynerTrade, 2024)

The platform digitizes procurement processes from sourcing to contract management. SynerTrade's e-tendering solution offers tools for managing electronic tenders, from RFP creation to bid evaluation. Automated scoring and comparative analysis support informed decision-making, while integration with contract management ensures a seamless procurement process (SynerTrade, 2024).

Basware: Basware focuses on e-invoicing and procure-to-pay solutions, automating procurement and finance operations (figure 9). Its platform streamlines purchasing workflows, reduces errors, and provides real-time spend visibility. Basware connects buyers and suppliers globally, ensuring regulatory compliance. Its e-tendering functionality supports tender creation, bid management, and automated evaluation within a centralized system. Integration with e-invoicing and payment solutions offers a seamless end-to-end procurement experience (Basware, 2024).

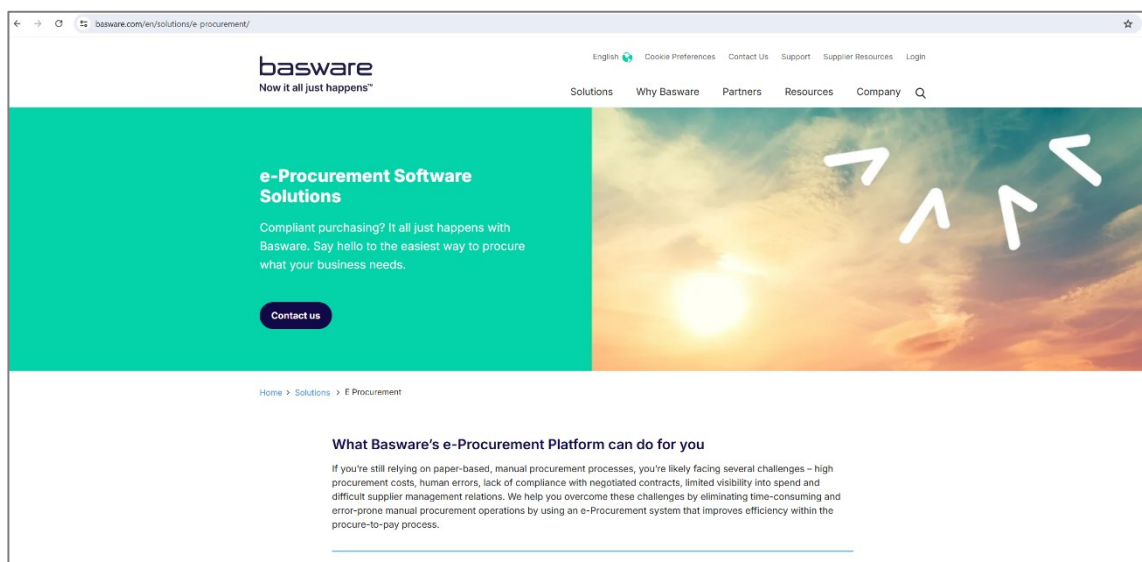


Figure 9. Basware webpage (Basware, 2024)

Procurify: Procurify is a procurement and spend management platform tailored for small to medium-sized businesses (figure 10). It offers tools for purchase requisitions, approvals, purchase orders, and expense management. The cloud-based solution simplifies procurement processes, providing real-time spending visibility and cost control. Procurify's e-tendering capabilities allow users to manage tenders, from creation to bid evaluation, ensuring compliance and cost-efficiency (Procurify, 2024).

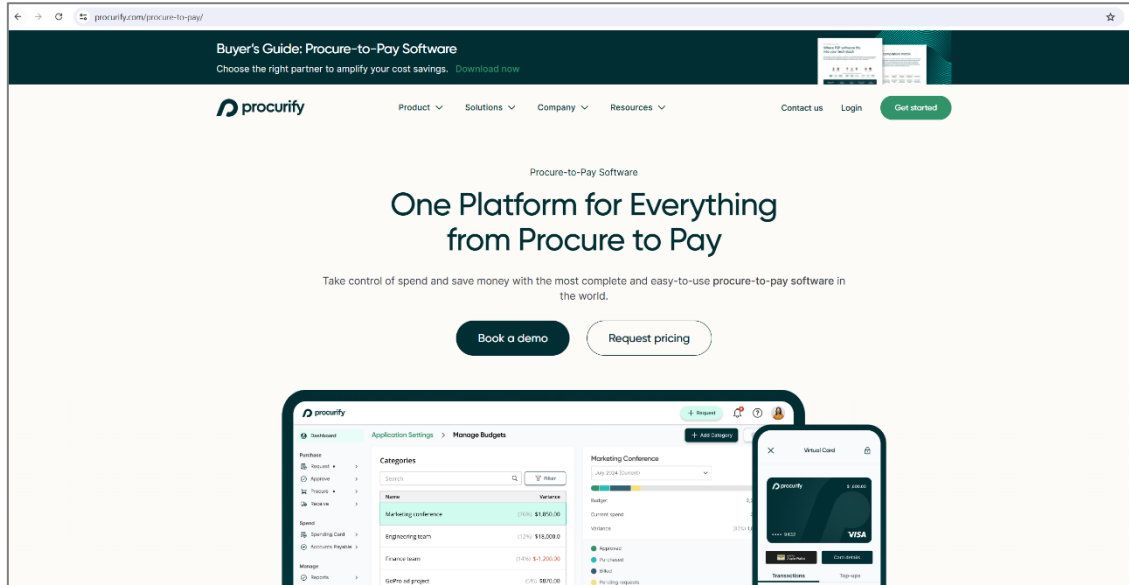


Figure 10. Procurify webpage (Procurify, 2024)

Merzell: Merzell is a Nordic e-procurement platform used extensively for public procurement (figure 11). It facilitates electronic tendering, contract management, and supplier collaboration, ensuring compliance and transparency in procurement activities. The platform manages the entire procurement lifecycle efficiently, from tender creation to contract execution. Merzell's e-tendering features include tender document creation, bid evaluation, and automated scoring, supporting fair and competitive bidding (Merzell, 2024).

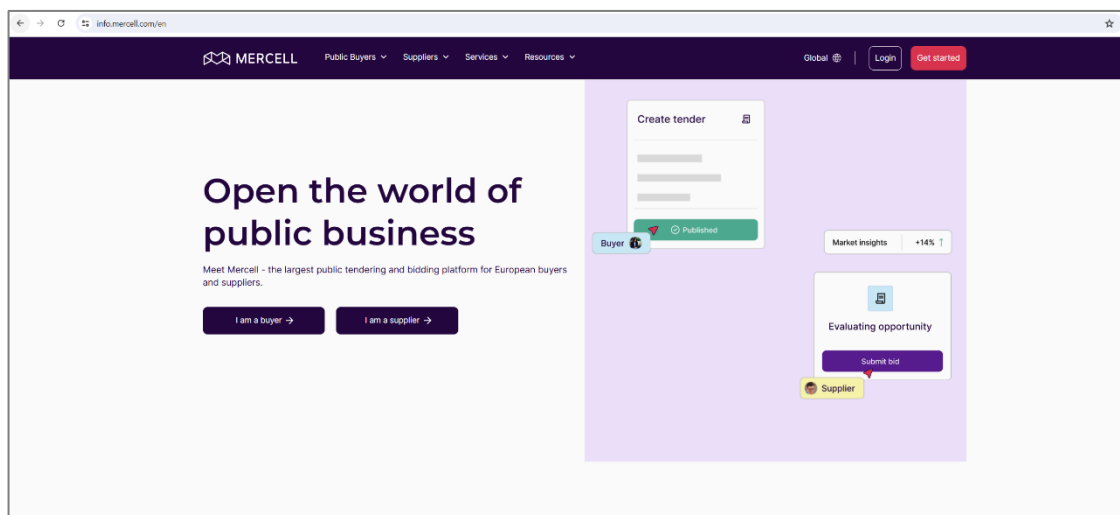


Figure 11. Merzell webpage (Merzell, 2024)

Zycus: Zycus offers a flexible suite of procurement solutions, including e-sourcing, procurement analytics, and supplier management (figure 12). Leveraging AI and machine learning, Zycus enhances procurement processes by automating tasks and providing actionable insights. Its modular design allows businesses to tailor their procurement capabilities for optimal efficiency and cost savings. The e-tendering module simplifies tender management by facilitating tender creation, bid distribution, automated bid evaluation, and supplier negotiations, ensuring transparency and compliance (Zycus, 2024).

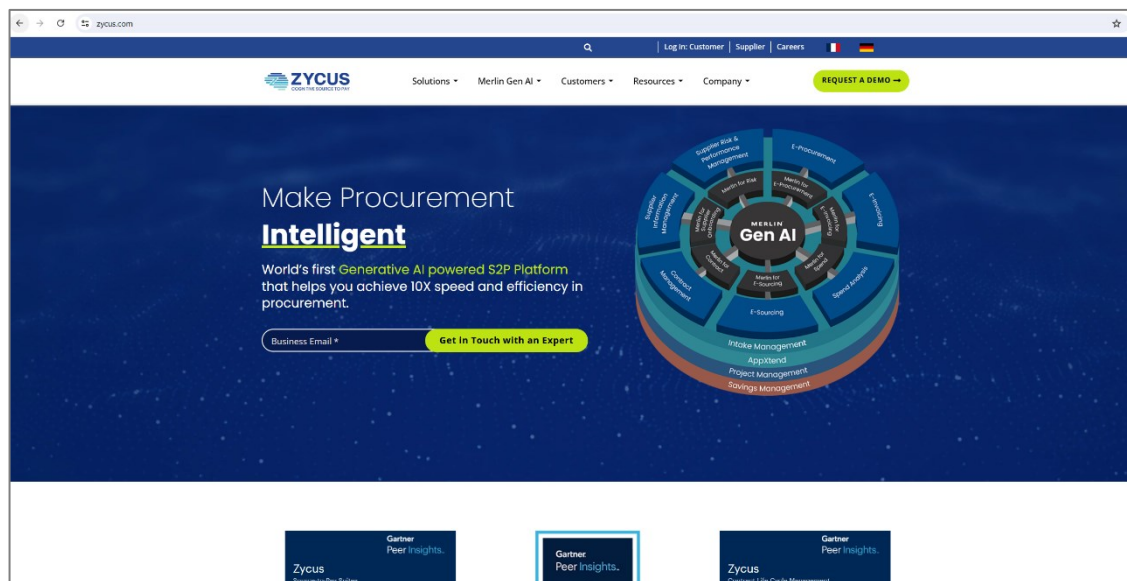


Figure 12. Zycus webpage (Zycus, 2024)

SoftOne: SoftOne Technologies continues to be a prominent player in the Greek market, offering a comprehensive suite of ERP, CRM, cloud services, and electronic invoicing solutions (figure 13). As of 2024, the company supports over 32,000 businesses across various countries, indicating substantial growth and innovation in their offerings. (SoftOne, 2024). SoftOne's latest product, the Soft1 Cloud ERP Series 6, provides an integrated solution that simplifies business operations by unifying critical business areas such as financial management, production, and supply chain processes. This system operates on Microsoft's Azure platform, ensuring high levels of security and reliability. Additionally, SoftOne's strategic investments have strengthened its market position. From 2019 to 2024, the company acquired several firms, including Unisoft, Prosvasis, Regate, IMPACT, cosmoONE, Global Sustain Technologies, Sunsoft, and Twinsoft. This expansion has positioned SoftOne as a leader in the Greek business software market, forming a group of companies that focus on business and accounting software solutions, innovative cloud

services, enterprise mobility applications, and electronic invoicing and procurement solutions.

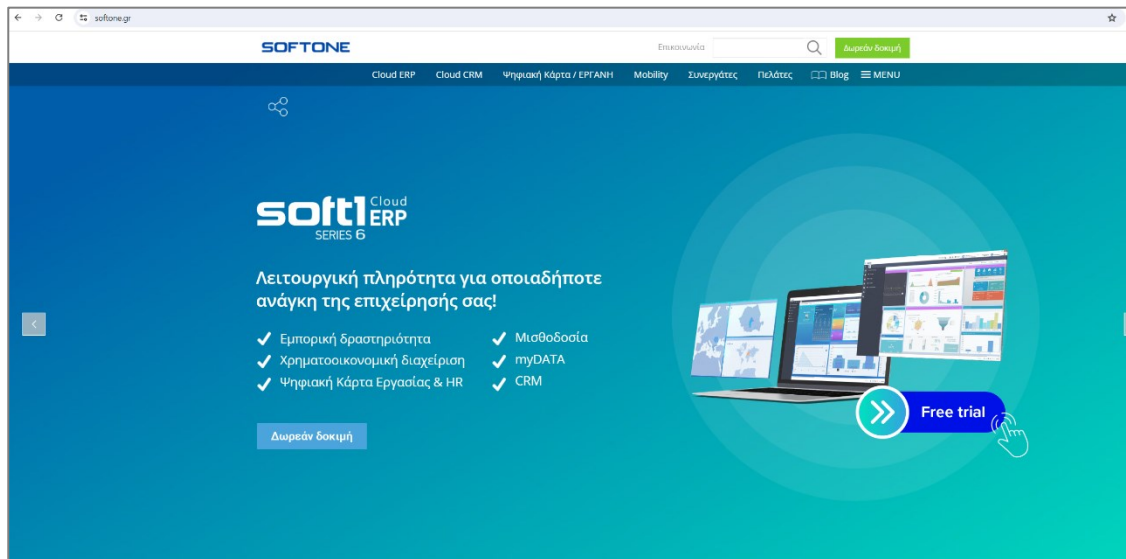


Figure 13. SoftOne webpage (SoftOne, 2024)

CosmoOne: CosmoOne is a leading Greek company, now part of the SoftOne Group, specializing in electronic procurement and electronic invoicing solutions (figure 14). Their platform is designed to streamline procurement processes, offering tools for supplier management, electronic tenders, and auction events. Known for its expertise in electronic procurement, CosmoOne optimizes the entire procurement lifecycle, from tender creation to contract execution. The platform includes functionalities for creating and managing electronic tenders, receiving bids, and automated bid evaluation, ensuring transparency and competitiveness (CosmoOne, 2024).



Figure 14. CosmoOne webpage (CosmoOne, 2024)

Entersoft: Entersoft is a prominent provider of enterprise software in Greece, offering a range of solutions including ERP, CRM, procurement, and supply chain management (figure 15). The Entersoft SCM360 suite streamlines supply chain processes, from procurement to warehousing and distribution. Entersoft’s solutions are flexible, scalable, and easily integrated with other enterprise systems, making them suitable for businesses of all sizes. The SCM360 platform includes e-tendering capabilities, allowing organizations to manage tender processes electronically, from publishing tenders to evaluating supplier bids, ensuring transparency and efficiency (Entersoft, 2024).



Figure 15. Entersoft webpage (Entersoft, 2024)

ESIDIS: ESIDIS is the National System of Electronic Public Procurement in Greece. It facilitates the electronic management of public procurement processes, ensuring compliance with national and EU regulations. ESIDIS supports the entire procurement lifecycle, from tender creation to contract management, enhancing transparency and efficiency in public procurement (ESIDIS, 2024; Interreg Europe, 2021; Drakopoulos Law, 2022; Public Procurement Laws and Regulations Report 2024 Greece, 2024).

TED: TED (Tenders Electronic Daily) is the official platform for public procurement in the European Union. It provides access to business opportunities from the EU, the European Economic Area, and beyond. TED facilitates the electronic tendering process, allowing businesses to access and respond to public procurement notices efficiently, ensuring transparency and compliance with EU regulations (Tenders Electronic Daily, 2024; European Commission, 2019).

EUPLAT: EUPLAT is the European Association of Public eTendering Platform Providers, aiming to promote the use of electronic tendering in public procurement across Europe. EUPLAT supports its members in developing and implementing e-tendering solutions that enhance transparency, competition, and efficiency in public procurement processes (EUPLAT, 2024).

2.3 Theoretical Background & Conceptual Framework

Understanding the adoption of e-tendering systems requires an examination of the theoretical underpinnings that explain how and why technological innovations are accepted and utilized within organizations. Several models and theories have been proposed over the years to explain technology adoption and one of the most comprehensive models is the Unified Theory of Acceptance and Use of Technology (UTAUT).

UTAUT integrates elements from eight foundational theories and models to provide a comprehensive framework for understanding technology adoption and usage behavior. These include the Theory of Reasoned Action (TRA) by Fishbein and Ajzen (1975), which focuses on the influence of attitudes and subjective norms on behavioral intentions, and the Technology Acceptance Model (TAM) by Davis (1989), which emphasizes perceived usefulness and perceived ease of use. The Motivational Model (MM) highlights the role of intrinsic and extrinsic motivation, while the Theory of Planned Behavior (TPB) by Ajzen (1991) adds perceived behavioral control to the mix. The Combined TAM and TPB (C-TAM-TPB) integrates aspects of both models, considering attitudes, subjective norms, and perceived behavioral control alongside perceived usefulness and ease of use. The Model of PC Utilization (MPCU) by Thompson et al. (1991) introduces factors such as job fit, complexity, and facilitating conditions. Rogers' (1995) Innovation Diffusion Theory (IDT) examines how innovations are adopted within social systems, considering attributes like relative advantage and compatibility. Lastly, Bandura's (1986) Social Cognitive Theory (SCT) focuses on self-efficacy, outcome expectations, and personal goals.

The UTAUT framework synthesizes these theories to explain user intentions and subsequent usage behavior of information systems. UTAUT identifies four key constructs: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions. Performance Expectancy is similar to TAM's perceived usefulness, Effort Expectancy aligns with TAM's perceived ease of use, Social Influence parallels the subjective norms in TRA and TPB, and

Facilitating Conditions are akin to perceived behavioral control in TPB. In addition to these constructs, UTAUT suggests that user behavior is moderated by gender, age, experience, and voluntariness of use. These moderators provide a nuanced understanding of how demographic and contextual factors influence technology adoption (Venkatesh et al., 2003). By integrating these foundational theories, UTAUT offers a robust framework for predicting and understanding the factors that lead to the adoption and continual use of technology within organizations.

The most significant theories contributing to UTAUT are the Theory of Reasoned Action (TRA), the Technology Acceptance Model (TAM), and the Theory of Planned Behavior (TPB).

2.3.1 Theory of Reasoned Action (TRA)

The Theory of Reasoned Action (TRA), introduced by Fishbein and Ajzen in 1975, is a seminal model in social psychology designed to predict intentional behavior. The central idea of TRA is that an individual's intention to engage in a particular behavior is the primary predictor of whether they will actually perform that behavior. These intentions are shaped by two key factors: attitudes toward the behavior and subjective norms.

Attitudes toward the behavior reflect an individual's positive or negative evaluations of performing the behavior. These attitudes are influenced by the person's beliefs about the outcomes of the behavior and the value they place on those outcomes. For example, if a person believes that adopting e-tendering systems will enhance procurement efficiency and views this improvement favorably, they are likely to develop a positive attitude towards using the technology.

Subjective norms pertain to the perceived social pressures to engage or not engage in a behavior. This factor is based on an individual's perception of the expectations of significant others, such as colleagues, superiors, or industry standards. If these influential figures endorse the use of e-tendering systems, the individual may feel a stronger social obligation to adopt the technology.

TRA has been pivotal in research on information technology (IT) adoption, offering a clear framework for understanding how users' beliefs impact their intentions and behaviors regarding technology use. Its straightforward approach has facilitated numerous studies, allowing researchers to explore the psychological foundations of technology acceptance.

For instance, studies have shown that individuals are more likely to adopt new technologies when they hold positive attitudes towards them and perceive that important others expect them to do so (Ajzen & Fishbein, 1980). Despite its broad applicability, TRA is somewhat limited by its focus on voluntary behaviors. The model assumes that individuals have full control over their actions, which may not always be true in real-world scenarios. In contexts where technology use is mandated or where significant external constraints exist, TRA may not fully capture the complexities influencing behavior. Nevertheless, TRA's focus on the interaction between personal attitudes and social influences remains relevant, continuing to inform contemporary models of technology adoption.

2.3.2 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), introduced by Davis in 1989, builds on the Theory of Reasoned Action (TRA) to better understand computer usage behavior. TAM simplifies the psychological constructs of TRA into two primary predictors: perceived usefulness and perceived ease of use. Perceived usefulness is defined as the extent to which an individual believes that using a particular system will enhance their job performance. In contrast, perceived ease of use refers to the extent to which a person believes that using the system will be free of effort.

Perceived usefulness reflects the degree to which an individual believes that utilizing a specific technology will improve their job performance. This perception is crucial because it directly impacts the user's motivation to adopt the technology. For example, if users believe that an e-tendering system will make procurement processes more efficient and accurate, they are more likely to perceive the system as useful and be inclined to adopt it.

Perceived ease of use, on the other hand, pertains to the degree of effort required to use the technology. If a system is perceived as user-friendly and easy to navigate, users are more likely to adopt it, as they do not anticipate significant difficulties in its operation. This aspect is particularly important during the initial stages of technology adoption, when users are forming their first impressions of the system.

TAM has gained considerable recognition for its applicability to various technological contexts and has been extensively validated across different technologies and user groups. Its focus on usability and utility as critical determinants of technology adoption has provided significant insights that have informed the development of subsequent models, including the

Unified Theory of Acceptance and Use of Technology (UTAUT). TAM emphasizes the importance of designing systems that are not only functionally effective but also easy to use, thereby reducing potential barriers to adoption. The simplicity and robustness of TAM have made it a foundational model in both academic research and practical applications. By providing a clear framework for predicting and enhancing user acceptance of new technologies, TAM has become a crucial tool for understanding how and why users decide to adopt or reject technological innovations. Its emphasis on perceived usefulness and perceived ease of use underscores the need for developers to focus on both the practical benefits of the technology and the user experience.

2.3.3 Theory of Planned Behavior

One of the most widely used models for predicting behavior in different areas is the Theory of Planned Behavior (TPB), introduced by Icek Ajzen in 1985 (Ajzen & Fishbein, 1980). TPB builds upon the earlier Theory of Reasoned Action (TRA), developed by Fishbein and Ajzen in 1975, by incorporating additional elements. This model aims to enhance the prediction of deliberate behavior by considering not only attitudes and subjective norms but also the perceived ease or difficulty of performing the behavior, reflecting past experiences and anticipated obstacles.

TPB argues that to predict behavior accurately, especially when individuals have limited control, one must consider not only the intention to perform the behavior but also the perceived control over that behavior (Ajzen & Madden, 1986). In TPB, behavior is directly related to the intention to perform the behavior, with the probability of performing the behavior increasing with stronger intentions (Ajzen, 1991). TPB introduces three distinct motivational factors for predicting behavioral intentions: attitude towards the behavior, subjective norms, and perceived behavioral control.

Attitude towards the behavior refers to the degree to which a person has a favorable or unfavorable evaluation of the behavior (Ajzen, 1991). This attitude is influenced by behavioral beliefs, which are perceptions about the consequences of performing the behavior and the positive or negative evaluations of these outcomes. For example, if a person believes that using an e-tendering system will streamline procurement processes and views this positively, they are likely to have a favorable attitude toward using the system.

Subjective norms refer to the social pressures that influence an individual's decision-making and engagement in behavior. These norms are determined by normative beliefs, which are the perceived expectations of significant others, such as family, friends and colleagues, and the individual's motivation to comply with these expectations. If an individual perceives that influential people or peers endorse the use of e-tendering systems, they may feel a stronger social obligation to adopt the technology.

Perceived behavioral control refers to an individual's perception of the resources and barriers that may facilitate or inhibit performance of the behavior, as well as their overall control over performing the behavior. This concept encompasses both internal factors, such as skills and abilities, and external factors, such as opportunities and constraints (Ajzen, 1991). For instance, if a user believes they have the necessary skills and organizational support to use an e-tendering system, they will perceive higher control over the behavior, thus increasing their intention to use the system.

TPB provides a more comprehensive understanding of behavior in real-world situations, where external factors often play a significant role. This makes TPB especially useful for predicting behaviors in environments where technology use may be influenced by both personal and contextual factors.

The relationship between behavior, intention, and the three variables suggested by the TPB model is illustrated in Figure 16.

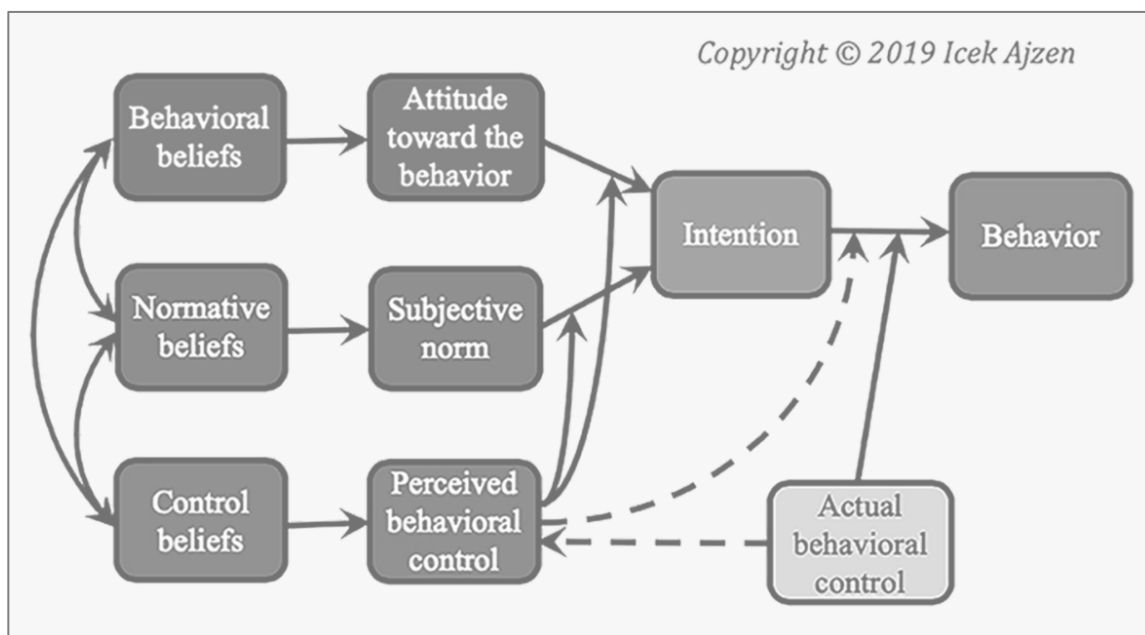


Figure 16. Research model of TPB (Ajzen, 2019)

2.3.4 Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) was developed to explain user intentions to use an information system and subsequent usage behavior. This theory combines components from eight earlier models that sought to explain technology adoption, including the Theory of Reasoned Action (TRA), the Technology Acceptance Model (TAM), the Motivational Model, and the Theory of Planned Behavior (TPB). Venkatesh et al. (2003) introduced UTAUT as a comprehensive solution to the inconsistencies and overlapping findings of earlier models. The development of UTAUT aimed to provide a unified framework by synthesizing fragmented findings from previous research, thus offering a more robust explanation for technology adoption behaviors. UTAUT posits that usage intention and behavior are influenced by four key constructs: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions.

Performance Expectancy, akin to TAM's perceived usefulness, is defined as the degree to which an individual believes that using the technology will help them achieve gains in job performance. This construct has been shown to be a crucial determinant of technology adoption, as it directly impacts the user's belief in the technology's effectiveness (Venkatesh et al., 2003).

Effort Expectancy reflects the degree of ease associated with the use of the technology, similar to TAM's perceived ease of use. It represents how easy or difficult the technology is perceived to be and is particularly significant during the early stages of technology adoption when users are still forming their initial impressions of the system (Venkatesh et al., 2003).

Social Influence measures the extent to which an individual perceives that important others believe they should use the new technology. This construct is derived from the subjective norm features of TRA and TPB, emphasizing the impact of social pressure on technology adoption decisions (Ajzen, 1991).

Facilitating Conditions refer to the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system. This construct parallels the perceived behavioral control in TPB, highlighting the importance of external resources and support systems in enabling technology use (Ajzen, 1991).

In addition to these main constructs, UTAUT suggests that user behavior is moderated by gender, age, experience, and voluntariness of use. These moderators can significantly

influence the impact of the core constructs on behavioral intention and use behavior, providing a more nuanced understanding of how different demographic and contextual factors affect technology adoption (Venkatesh et al., 2003). For example, the impact of Performance Expectancy might vary with age, as older users may value performance benefits differently compared to younger users (Morris & Venkatesh, 2000).

Use Behavior is conceptualized as the outcome of the model, aiming to predict and understand the factors that lead to the actual adoption and continual use of a technology within a company or by individual users. Use Behavior is directly influenced by Behavioral Intention and Facilitating Conditions. Behavioral Intention, one of the strongest predictors of Use Behavior, represents the degree to which a person has formulated conscious plans to perform or not perform some specified future behavior. It encapsulates the motivational factors influencing an individual's decision to use a technology and is typically predicted by Performance Expectancy, Effort Expectancy, and Social Influence (figure 17).

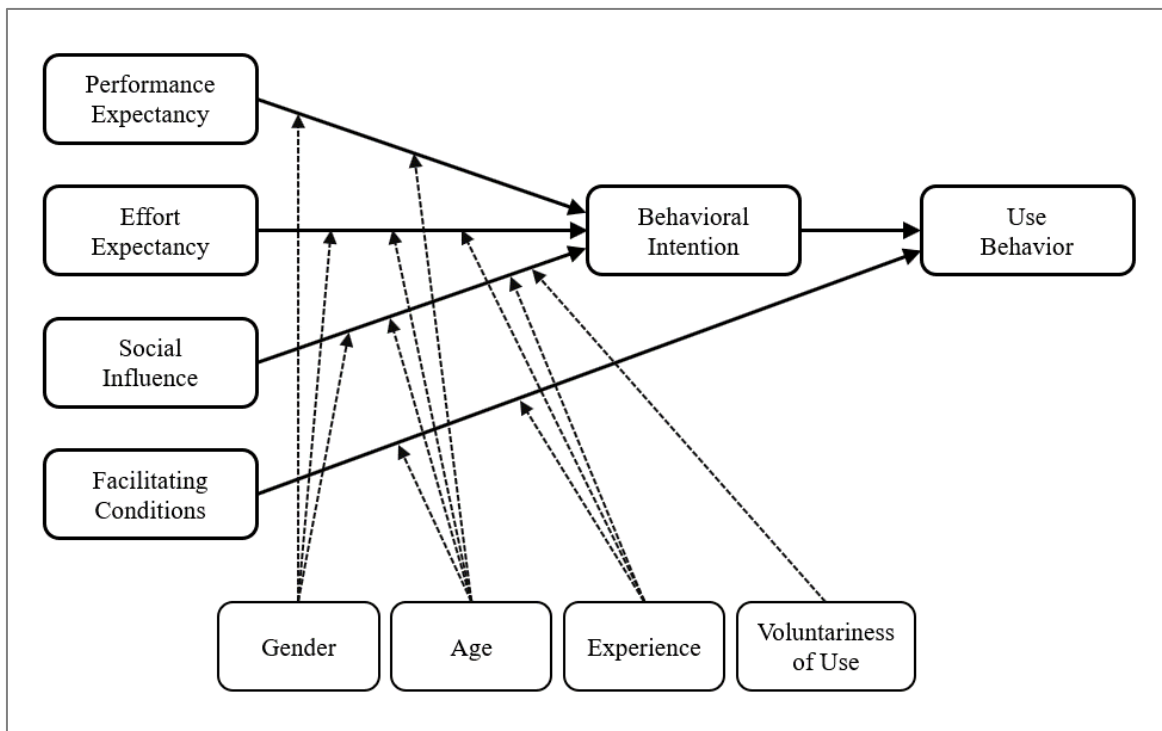


Figure 17. Research model of UTAUT (Venkatesh et al., 2003)

2.4 Research Hypotheses

The Unified Theory of Acceptance and Use of Technology (UTAUT) has been widely applied across various contexts and technologies, demonstrating its robustness and adaptability. From e-government systems to e-health services, the UTAUT model has

consistently provided valuable insights into technology adoption behaviors. Numerous studies have leveraged UTAUT to explore the adoption of mobile banking, e-learning, and online shopping technologies, underscoring the theory's broad applicability and relevance (Venkatesh et al., 2003).

For the current research, the UTAUT model serves as the conceptual backbone. The model's constructs are hypothesized to influence both the behavioral intention to use e-tendering applications and their actual usage among Greek companies. The application of UTAUT in this context aims to reveal insights into the factors that influence the adoption and use of e-tendering applications by Greek companies, which are critical for streamlining procurement processes in the digital age.

Thus, the hypotheses are structured around the core constructs of the UTAUT model: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC). Each construct's impact on Behavioral Intention (BI) and Use Behavior (UB) is hypothesized, reflecting their direct and mediated effects on technology adoption.

Performance Expectancy (PE): This construct refers to the degree to which an individual believes that using the technology will help them achieve gains in job performance. Numerous studies have highlighted the significance of performance expectancy as a predictor of behavioral intention across various technological domains. Venkatesh et al. (2012) demonstrated that performance expectancy significantly influenced the adoption of mobile banking services. Their findings indicated that users who believed mobile banking would enhance their financial management were more likely to adopt and use these services. Similarly, research by Šumak, Heričko, and Pušnik (2011) in the context of e-learning adoption showed that performance expectancy played a vital role in shaping users' intentions to engage with e-learning platforms. Users who perceived that e-learning would improve their educational outcomes were more inclined to use these technologies. Further supporting the importance of performance expectancy, studies in other domains have yielded consistent results. For instance, research on e-government services by Shareef et al. (2011) found that performance expectancy was a significant predictor of citizens' intentions to use e-government services. The study emphasized that when individuals perceived that e-government services would enhance their efficiency in accessing government-related information and services, their intention to use these services increased. In the healthcare sector, performance expectancy has also been identified as a critical factor. Chau and Hu

(2001) investigated physicians' acceptance of telemedicine technology and found that performance expectancy significantly influenced their intention to adopt telemedicine systems. Physicians who believed that telemedicine would improve their diagnostic and treatment capabilities were more likely to integrate these systems into their practice. Vaidya, Sajeev, and Callender (2006) conducted a comprehensive study on the critical factors that affect the adoption of e-procurement systems in the public sector. They found that performance expectancy, in terms of improved procurement efficiency and cost savings, was a significant predictor of user intention to adopt e-procurement systems. Zailani, Ramayah, and Moganavally (2008) explored the factors influencing the adoption of e-tendering systems in Malaysian construction firms. Their findings indicated that performance expectancy, such as perceived improvements in project management and transparency, significantly impacted the intention to use e-tendering systems. A study by Gunasekaran and Ngai (2008) investigated e-procurement adoption among small and medium-sized enterprises (SMEs) and found that performance expectancy, specifically in terms of operational efficiencies and cost savings, was a crucial determinant of adoption intention. Basu and Steve (2007) examined the adoption of e-procurement systems in multinational corporations. They found that performance expectancy, including improved supply chain management and cost efficiencies, significantly influenced the decision to adopt e-procurement technologies. Other recent studies have also validated the importance of performance expectancy. For instance, a study by Maduku, Mpinganjira, and Duh (2016), the UTAUT model was employed to investigate the adoption of e-procurement systems in South African supply chains. The results indicated that performance expectancy, particularly in terms of improved supply chain integration and process efficiency, was a major determinant of adoption. A study by Baptista and Oliveira (2015) on mobile banking adoption in Brazil found that performance expectancy was a significant predictor of intention to use mobile banking services. Similarly, a study by Alshehri, Drew, and Alfarraj (2012) on e-government services in Saudi Arabia confirmed that performance expectancy was a major determinant of user acceptance. Additionally, research by Raman and Don (2013) on e-learning adoption in Malaysian higher education institutions emphasized the role of performance expectancy in shaping students' intentions to use e-learning systems. In the context of e-tendering applications, performance expectancy might include perceived improvements in procurement efficiency, cost savings, and enhanced transparency in procurement processes. These improvements are crucial in procurement environments where efficiency and accountability are paramount.

Thus, it is hypothesized:

- **Hypothesis 1 (H1):** Performance expectancy positively affects the behavioral intention to use e-tendering applications.

Effort Expectancy (EE): This construct represents the perceived ease of use associated with the technology. Various studies have explored the impact of effort expectancy on technology adoption across different domains, consistently demonstrating its importance as a predictor of behavioral intention. In Davis' (1989) work on the Technology Acceptance Model, perceived ease of use (akin to effort expectancy) was found to be a significant determinant of users' attitudes towards and intentions to use information technology. This foundational study established the critical role of ease of use in technology adoption. Venkatesh et al. (2003) further validated the significance of effort expectancy in their development of the UTAUT model. They found that effort expectancy was a strong predictor of behavioral intention to use a variety of technologies, underscoring the importance of ease of use in user acceptance. Choudrie and Dwivedi (2005) explored e-government adoption in the UK and found that effort expectancy significantly influenced user acceptance of e-government services. This study highlighted the importance of ease of use in encouraging citizens to engage with online government services. Vaidya, Sajeew, and Callender (2006) found that effort expectancy was also a significant predictor of user intention to adopt e-procurement systems. The study highlighted that perceived ease of use was crucial in encouraging procurement professionals to engage with e-procurement technologies. A study by Zailani, Ramayah, and Moganavally (2008) explored the factors influencing the adoption of e-tendering systems in Malaysian construction firms. The findings indicated that effort expectancy significantly impacted the intention to use e-tendering systems. The perceived ease of using the e-tendering system was a critical determinant in the adoption decision. Holden and Karsh (2010) examined the acceptance of healthcare information systems and found that effort expectancy significantly influenced healthcare professionals' intentions to use these systems. Ease of use was a major factor in the adoption of healthcare technologies, impacting both initial acceptance and continued use. Venkatesh, Thong, and Xu (2012) confirmed that effort expectancy significantly influenced users' intentions to adopt mobile banking services. Users who perceived mobile banking as easy to use were more likely to intend to use these services, highlighting the relevance of effort expectancy in the financial technology domain. Al-Marroof and Al-Emran (2018) investigated the adoption of Google Classroom and found that effort expectancy was

a significant predictor of students' behavioral intention to use the platform. Their findings suggested that when students found Google Classroom easy to use, they were more likely to engage with it for their educational needs. A study by Jeong and Yoon (2013) on smartphone application adoption highlighted the role of effort expectancy in influencing users' behavioral intentions. They found that users were more likely to adopt smartphone apps that they perceived as easy to use, reinforcing the importance of effort expectancy in the mobile app domain. Zhang et al. (2017) examined the acceptance of electronic health records (EHRs) among healthcare professionals and found that effort expectancy significantly influenced their intentions to use EHR systems. The study emphasized that when healthcare professionals perceived EHRs as easy to use, they were more likely to adopt them. In a study by Maduku, Mpinganjira, and Duh (2016), the UTAUT model was employed, and the results indicated that effort expectancy, particularly the ease of integrating e-procurement into existing processes, was a major determinant of adoption. In the context of e-tendering applications, if users find these applications easy to learn and use, they are more likely to adopt them.

Hence, it is hypothesized:

- **Hypothesis 2 (H2):** Effort expectancy positively affects the behavioral intention to use e-tendering applications.

Social Influence (SI): This construct involves the extent to which individuals perceive that important others (such as colleagues, supervisors, or industry peers) believe they should use the new technology. Social influence is particularly significant in organizational settings where peer opinions and managerial support can strongly affect technology adoption (Venkatesh & Davis, 2000). Venkatesh et al. (2003) established social influence as a significant predictor of behavioral intention in their development of the UTAUT model. They demonstrated that social influence affects users' intentions to adopt a variety of technologies by incorporating social norms and pressures from significant others. Venkatesh, Thong, and Xu (2012) found that social influence significantly influenced users' intentions to adopt mobile banking services. Users who perceived that important others believed they should use mobile banking were more likely to adopt these services, highlighting the impact of social norms and peer pressure. Alshare and Lane (2011) explored the adoption of e-learning technologies and found that social influence significantly impacted students' intentions to use e-learning platforms. The study suggested that students were more likely to adopt e-learning if they perceived social approval from peers and

instructors. Hameed, Counsell, and Swift (2012) investigated the adoption of e-tendering systems in the UK construction industry using the UTAUT model. Their study confirmed that social influence, including the perceived pressure from influential stakeholders, significantly impacted the intention to use e-tendering systems. Research by Kamaruddin and Udin (2019) applied the UTAUT model to study e-procurement adoption in Malaysian SMEs. Social influence was identified as a critical factor, with users perceiving significant pressure from business partners and competitors to adopt e-procurement systems. In a study by Chang, Wong, and Loke (2018), the UTAUT model was employed to investigate the adoption of e-procurement systems in Singaporean supply chains. The results indicated that social influence, particularly the influence of suppliers and customers, was a major determinant of adoption. Chau and Hu (2001) investigated physicians' acceptance of telemedicine technology and found that social influence significantly influenced their intention to adopt telemedicine systems. Physicians who perceived that their peers and colleagues endorsed telemedicine were more likely to integrate these systems into their practice. Vaidya, Sajeew, and Callender (2006) also found that social influence, such as the support from higher management and peer endorsement, was a significant predictor of user intention to adopt e-procurement systems. Zailani, Ramayah, and Moganavally (2008) explored the factors influencing the adoption of e-tendering systems in Malaysian construction firms. Their findings indicated that social influence, such as the perceived endorsement from industry peers and stakeholders, significantly impacted the intention to use e-tendering systems. In the context of e-tendering applications, if key stakeholders within a company advocate for e-tendering applications, employees are more likely to adopt these systems. Thus, the following hypothesis is proposed:

- **Hypothesis 3 (H3):** Social influence positively affects the behavioral intention to use e-tendering applications.

Behavioral Intention (BI): Behavioral intention is a central mediator in the UTAUT model, predicting the actual use of technology. It encapsulates the motivational factors that influence an individual's decision to use a technology. Prior research has consistently demonstrated that behavioral intention is one of the strongest predictors of use behavior (Ajzen, 1991; Venkatesh et al., 2003). The foundational study that introduced the UTAUT model emphasized that behavioral intention is a strong predictor of actual technology use. Their findings across different organizational contexts validated that when individuals have a high intention to use a technology, they are more likely to engage in actual usage. In their

extension of the UTAUT model to consumer contexts, specifically mobile internet services Venkatesh, Thong, and Xu (2012) found that behavioral intention significantly predicted actual usage. The study highlighted that intentions formed based on performance expectancy, effort expectancy, and social influence translate into real behavior. A meta-analytic review of UTAUT applications by Taiwo and Downe (2013) confirmed the critical role of behavioral intention in predicting actual usage. By synthesizing findings from multiple empirical studies, they demonstrated that behavioral intention consistently leads to actual technology use, reinforcing the robustness of this relationship. A comprehensive literature review of UTAUT applications across various domains by Williams, Rana, and Dwivedi (2015) highlighted numerous studies where behavioral intention significantly predicted actual usage behavior, validating the model's efficacy and reliability. Al-Shafi and Weerakkody (2010) applied the UTAUT model to investigate the adoption of e-government services in Qatar. They found that behavioral intention significantly predicted actual usage, emphasizing that strong intentions formed by citizens led to increased engagement with e-government platforms. Teo (2011) studied the acceptance of e-learning technologies among teachers and confirmed that behavioral intention was a significant predictor of actual usage. Teachers who expressed strong intentions to use e-learning were more likely to integrate these technologies into their teaching practices. Ifinedo (2012) which used the UTAUT model to explore the adoption of systems found that behavioral intention significantly influenced actual usage, with professionals who intended to use the systems being more likely to incorporate them into their daily workflows. Zhou, Lu, and Wang (2010) investigated mobile banking adoption in China using the UTAUT model. They found that behavioral intention was a critical predictor of actual usage, with customers who intended to use mobile banking services being more likely to adopt and utilize these services. Pavlou and Fygenson (2006) extended the Theory of Planned Behavior (a precursor to UTAUT) to examine e-commerce adoption. They found that behavioral intention significantly predicted actual online purchasing behavior, supporting the notion that strong intentions translate into real actions. Marchewka, Liu, and Kostiwa (2007) applied the UTAUT model to study the adoption of ERP systems in higher education. Their findings indicated that behavioral intention was a crucial determinant of actual usage, reinforcing the idea that intentions are strong predictors of behavior. Therefore, it is hypothesized:

- **Hypothesis 4 (H4):** Behavioral intention positively affect the actual use of e-tendering applications.

Facilitating Conditions (FC): This construct refers to the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system. This includes the availability of resources, training, and support necessary for effective technology usage. Facilitating conditions have been found to significantly influence the actual use of technology, particularly when adequate support and resources are provided (Venkatesh et al., 2003). In their work introducing the UTAUT model, Venkatesh et al. (2003) found that facilitating conditions significantly predicted actual technology use. Their research demonstrated that when users perceive strong support and infrastructure for a technology, they are more likely to engage in its actual use. Venkatesh, Thong, and Xu (2012) study found also that facilitating conditions significantly influenced actual usage. The study highlighted the importance of having adequate resources and support for users to effectively use the technology. Williams, Rana, and Dwivedi (2015) comprehensive review of UTAUT applications across various domains reinforced the importance of facilitating conditions in predicting actual usage. Furthermore, empirical research by Marchewka, Liu, and Kostiwa (2007) applied the UTAUT model to e-learning environments and found that facilitating conditions such as technical support and training were critical factors influencing students' actual use of the e-learning system. This indicates that providing robust support mechanisms can enhance the adoption and utilization of technology. Additionally, recent studies in the context of e-procurement have also highlighted the role of facilitating conditions. For instance, Chang, Wong, and Park (2019) examined the adoption of e-procurement systems in the public sector and found that facilitating conditions, including the availability of training programs and IT support, significantly influenced the actual use of these systems. This research supports the argument that adequate support structures are essential for the effective use of e-procurement technologies. In a study by Alalwan, Dwivedi, and Williams (2016), facilitating conditions were found to significantly impact the actual use of mobile banking applications. Their research indicated that user-friendly interfaces and reliable technical support were crucial in encouraging users to adopt and continuously use these applications, underscoring the role of facilitating conditions in technology adoption. Similarly, a study by Hassan (2021) on the adoption of e-learning during the COVID-19 pandemic found that facilitating conditions such as access to technology and technical support were critical in ensuring the effective use of e-learning platforms. The consistent findings across various studies and contexts emphasize that facilitating conditions are crucial determinants of actual technology use. Whether in e-learning, mobile banking, or e-procurement, the presence of robust support

mechanisms, adequate training, and reliable infrastructure significantly enhances users' ability to adopt and effectively use technological systems. Therefore, it is hypothesized:

- **Hypothesis 5 (H5):** Facilitating conditions positively affects the actual use of e-tendering applications.

Demographic (Gender, age, etc), experience, and voluntariness of use are posited to moderate the impact of the four key constructs (PE, EE, SI and FC) on usage intention (BI) and behavior (UB). To explore these moderating effects, the following hypotheses are formulated.

Gender: Gender differences can influence technology adoption, as men and women may have different attitudes and responses to new technologies. Research indicates that gender can moderate the effects of performance expectancy, effort expectancy, and social influence on behavioral intention (Venkatesh & Morris, 2000). Venkatesh et al. (2003) found that men are more influenced by performance expectancy, while women are more influenced by effort expectancy and social influence. This gender-based differentiation underscores the need for tailored approaches when implementing new technologies to ensure effective adoption across both genders. Subsequent studies have reinforced these findings. For instance, a study by Venkatesh, Thong, and Xu (2012) found that gender significantly moderated the effects of the core constructs on behavioral intention. Specifically, the study confirmed that performance expectancy had a stronger effect on men, while effort expectancy and social influence had stronger effects on women. In the context of e-learning, Ong and Lai (2006) investigated gender differences in the acceptance of e-learning systems using an extended TAM model. Their study revealed that men and women differed in their perceptions of ease of use and usefulness, which in turn affected their behavioral intentions to use e-learning technologies. Men were more driven by perceived usefulness (aligned with performance expectancy), while women placed greater emphasis on perceived ease of use (aligned with effort expectancy). Moreover, a study by Ahuja and Thatcher (2005) examining gender differences in internet use among employees found that social influence had a more significant impact on women's intention to use the internet compared to men. This aligns with the notion that women are more susceptible to social factors when it comes to technology adoption, highlighting the moderating role of gender. In summary, gender significantly moderates the effects of performance expectancy, effort expectancy, and social influence on behavioral intention. This moderation suggests that men and women respond

differently to these factors when deciding to adopt new technologies. Thus, it is hypothesized:

- **Hypothesis 6 (H6):** Gender significantly moderates the effects of performance expectancy, effort expectancy, and social influence on the behavioral intention.

Age: Age can also play a significant role in technology adoption, with younger individuals generally being more comfortable with digital technologies. Age differences can moderate the effects of performance expectancy, effort expectancy, and social influence on behavioral intention (Morris & Venkatesh, 2000). Venkatesh, Thong, and Xu (2012) found that age moderated the effects of performance expectancy and effort expectancy on behavioral intention. Their study indicated that younger users prioritized performance-related outcomes, while older users were more concerned with the ease of use and social influences. Similarly, Morris, Venkatesh, and Ackerman (2005) found that older adults were more influenced by effort expectancy and social influence, whereas younger adults were primarily driven by performance expectancy in their decision to adopt new technology. Furthermore, Morris, Venkatesh, and Ackerman (2005) highlighted that older adults benefitted more from facilitating conditions such as training and technical support compared to younger adults. This suggests that providing adequate support structures is essential to ensure the effective use of technology among older users. research by Shareef et al. (2011) demonstrated that older adults were more dependent on facilitating conditions like user training and helpdesk support to effectively use these services. The study emphasized the importance of targeted interventions to address the specific needs of older users in technology adoption. In summary, age significantly moderates the effects of performance expectancy, effort expectancy, and social influence on behavioral intention, as well as the effects of facilitating conditions on the actual use of e-tendering applications. Therefore, it is hypothesized:

- **Hypothesis 7 (H7):** Age significantly moderates the effects of performance expectancy, effort expectancy, and social influence on the behavioral intention.
- **Hypothesis 8 (H8):** Age significantly moderates the effects of facilitating conditions on the actual use of e-tendering applications.

These hypotheses explore how demographic factors such as gender and age influence the strength and direction of the relationships posited by the UTAUT model.

Experience: Experience with similar technologies can enhance or diminish the perceived ease of use, thereby affecting adoption decisions. Experienced users might find it easier to

adapt to new systems, which can moderate the effects of effort expectancy and social influence on behavioral intention (Taylor & Todd, 1995). The UTAUT model indicates that individuals with prior experience are more likely to have lower effort expectancy and be less influenced by social pressures when adopting new technologies (Venkatesh et al., 2003). Furthermore, Venkatesh, Thong, and Xu (2012) found that experience significantly moderated the effects of effort expectancy and social influence on behavioral intention to use mobile internet services. Their research demonstrated that users with more experience perceived the technology as easier to use and were less swayed by others' opinions. Venkatesh et al. (2003) suggested that experienced users are better at leveraging facilitating conditions to their advantage, making them more likely to use the technology effectively. This is supported by Thompson, Higgins, and Howell (1994), who found that experience with prior technologies moderated the impact of facilitating conditions on the use of personal computers in organizations. In summary, experience with similar technologies significantly moderates the effects of effort expectancy and social influence on behavioral intention, as well as the effects of facilitating conditions on the actual use of e-tendering applications. Hence, it is hypothesized:

- **Hypothesis 9 (H9):** Experience with similar technologies significantly moderates the effects of effort expectancy and social influence on the behavioral intention.
- **Hypothesis 10 (H10):** Experience of use significantly moderates the effects of facilitating conditions on the actual use of e-tendering applications.

Voluntariness of Use: Whether employees feel they have a choice about using the technology can impact how social pressures influence adoption outcomes. If the use of e-tendering applications is perceived as voluntary, social influence may have a stronger effect on behavioral intention (Hartwick & Barki, 1994). The UTAUT model incorporates voluntariness of use as a moderating factor, suggesting that when technology use is perceived as voluntary, the impact of social influence on behavioral intention is heightened (Venkatesh et al., 2003). Venkatesh and Davis (2000) found that voluntariness significantly moderated the relationship between social influence and intention to use technology. Their study indicated that when employees perceived the use of a system as voluntary, social influence had a stronger impact on their intention to use the technology. This is because voluntary usage conditions make social norms and peer influences more salient. Further research by Venkatesh, Thong, and Xu (2012) confirmed that voluntariness of use moderated the effects of social influence on the adoption of mobile internet services. Their

findings suggested that in contexts where technology use was voluntary, social pressures from peers and superiors had a more pronounced effect on behavioral intentions. In summary, voluntariness of use significantly moderates the effect of social influence on behavioral intention. Therefore, it is hypothesized:

- **Hypothesis 11 (H11):** Voluntariness of use significantly moderates the effects of social influence on the behavioral intention.

The research model is presented below in figure 18.

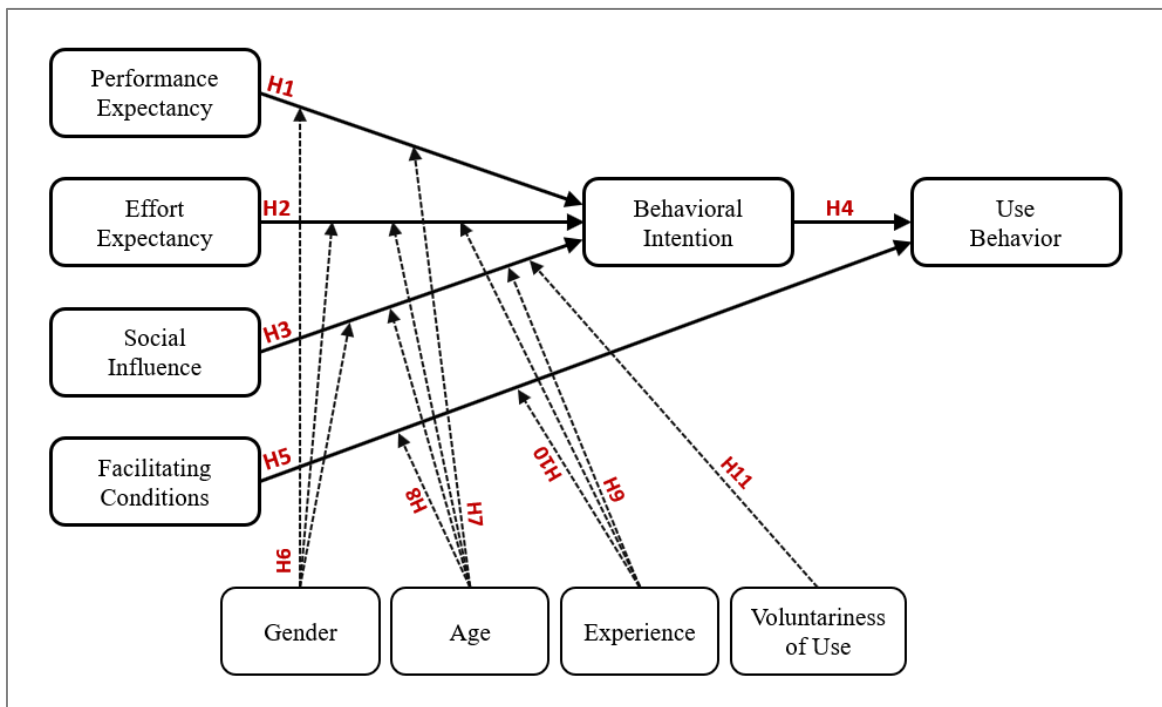


Figure 18. Research hypothesis direction

Testing these hypotheses will provide a comprehensive analysis of the factors influencing the adoption of e-tendering applications in Greek companies. By understanding these relationships, organizations can better tailor their technology implementation strategies, ensuring higher adoption rates and optimal usage. Furthermore, the results will contribute to the broader literature on technology adoption, particularly in the context of e-tendering systems, and refine the theoretical constructs of the UTAUT model for future research in similar contexts.

Chapter 3: Research Methodology

3.1 Research method

Conducting research to answer specific questions necessitates the use of scientifically rigorous methodologies and procedures. Quantitative and qualitative research are the most common research approaches. Quantitative research involves the collection and analysis of numerical data through statistical tools, providing an objective assessment of the phenomena being studied. Conversely, qualitative research explores social phenomena that are challenging to quantify, such as attitudes, emotions, and perceptions, thereby offering a more subjective perspective (Creswell & Creswell, 2018).

Quantitative methods are often characterized by their emphasis on measurement and testing hypotheses through structured data collection and statistical analysis. This approach is ideal for studies that require numerical validation and the identification of patterns or relationships among variables (Bryman, 2016). In contrast, qualitative methods are used to gain a deeper understanding of complex social phenomena by analyzing non-numerical data such as interviews, observations, and textual analysis, allowing researchers to capture the richness of human experience and context (Denzin & Lincoln, 2011).

In some research contexts, a mixed methods approach is employed, combining both quantitative and qualitative techniques to leverage the strengths of each. This approach can provide a more comprehensive understanding of the research problem by integrating numerical data with detailed contextual insights (Tashakkori & Teddlie, 2010).

3.2 Data collection and sampling

To address a research problem effectively, a researcher must gather both quantitative and qualitative data from pertinent sources. Primary data, which is collected firsthand through methods such as surveys, interviews, observations, is directly obtained by the researcher. Primary data is invaluable for obtaining specific, detailed information that directly addresses the research hypotheses or questions. This data is often more accurate and reliable because it is gathered directly from the source and tailored to the study's needs. Secondary data, on the other hand, is sourced from existing records or documents created by other researchers or institutions, providing a broader context that can support primary findings (Saunders, Lewis, & Thornhill, 2016). Thus, secondary data while potentially less specific, can offer

valuable background information. It is also more cost-effective and time-efficient, making it a useful resource for exploratory research or preliminary stages of a study (Bryman, 2016). The choice of research methodology inherently determines the data collection approach. Qualitative research typically involves collecting data through interviews with a small, targeted group, allowing for in-depth exploration of complex phenomena that are difficult to quantify, such as personal experiences, opinions, and social processes (Creswell & Poth, 2018). On the other hand, quantitative research relies heavily on questionnaires to gather data from a larger sample, facilitating statistical analysis.

The terms "population" and "sample" are fundamental in research design. The term "population" refers to the entire group under study, while "sample" denotes a subset of that population. Selecting an appropriate sampling method is crucial, as it ensures that the research findings are representative of the population and that the conclusions drawn are valid. Sampling methods are broadly classified into probability and non-probability sampling. In probability sampling, every individual in the population has a known and equal chance of being selected, making it possible to generalize findings to the entire population with a high degree of confidence (Cochran, 1977). Non-probability sampling, however, does not provide each individual with a known probability of selection, which can introduce bias but is often faster and more cost-effective (Saunders et al., 2007, 2009).

Probability sampling techniques, such as simple random sampling, are valued for their ability to support robust statistical inferences about the population. Non-probability sampling techniques, like convenience sampling, are practical in situations where probability sampling is not feasible due to constraints like time, cost, or accessibility. Despite the higher risk of sampling bias associated with non-probability sampling, this method can be beneficial in exploratory research or preliminary studies where the focus is on gaining insights rather than making broad generalizations (Etikan, Musa, & Alkassim, 2016).

Determining the appropriate sample size is a crucial element in the sampling process. One fundamental principle is that larger sample sizes are generally advantageous, as they enhance statistical power and reduce sampling error, leading to more accurate and representative results (Cochran, 1977; Field, 2018). Statistical power refers to the probability of correctly rejecting a false null hypothesis, and it increases with the sample size. This means that studies with larger samples are more likely to detect significant effects if they exist. A large sample size also helps to ensure that the sample accurately reflects the

population, capturing its diversity and thereby increasing the generalizability of the findings. This representativeness is vital for making valid inferences about the entire population based on the sample data. In essence, as the sample size grows, the margin of error decreases, and the confidence in the results improves, making the conclusions drawn more robust and credible (Krejcie & Morgan, 1970). Despite these advantages, practical constraints such as time, budget, and resources often limit the feasible sample size. Researchers must balance these constraints with the need for statistical reliability. While larger samples are ideal for minimizing sampling error and enhancing representativeness, researchers should aim for a sample size that is both sufficient to achieve the study's objectives and manageable within practical limitations (Bryman, 2016).

For the purpose of this study, a quantitative research method was utilized, with primary data collected via a self-administered online questionnaire. The questionnaire targeted professionals in the Greek private sector who are involved in procurement or manage digital procurement solutions. Data collection took place via email from April 23, 2024, to May 19, 2024. The survey was distributed to over 4,400 email addresses, predominantly sourced from public directories such as the Athens Chamber of Commerce & Industry (ACCI) and the General Commercial Registry of Greece (GEMI). Despite the extensive distribution effort, more than 500 emails were not delivered due to outdated contact information. Consequently, it is estimated that the survey successfully reached the mailboxes of over 3,900 recipients. To maximize response rates, follow-up emails were sent throughout the survey period to remind and encourage participation. Participation was entirely voluntary, and no incentives were offered to respondents.

The sampling method employed for this research was a non-probability sampling technique, specifically random convenience sampling. This method combines elements of both convenience and random sampling. While the convenience aspect involved selecting participants based on their accessibility and availability — targeting professionals within Greek companies — the emails were sent out randomly across the target population. This method combines the practicality of convenience sampling with a random distribution approach to enhance the diversity and representativeness of the sample. The survey's random distribution within the convenience framework helps mitigate some of the biases typically associated with convenience sampling. By not specifying selection criteria beyond the involvement in procurement or digital procurement solutions, the sampling aimed to capture a broad spectrum of professionals within the defined population. Overall, this mixed

approach allowed for efficient data collection while aiming to obtain a representative sample of the target population, providing valuable insights into the adoption of e-tendering applications among Greek companies. The methodology ensured that, despite practical constraints, the data collected was robust and provided a robust foundation for analyzing the factors influencing the adoption and use of digital procurement solutions, and also a valuable foundation for future, more extensive research.

For this study, a sample of 117 responses was collected, representing a response rate of approximately 3%. This low response rate is a common issue in survey research, especially within business contexts where professionals may have limited time or interest in participating. Despite extensive efforts to maximize participation, including follow-up emails and making the survey as accessible as possible, the response rate remained low. This situation likely necessitates a further discussion of potential non-response bias, where the views of respondents may not accurately reflect those of the broader population. This bias can compromise the reliability and validity of the study's conclusions. To mitigate its effects, researchers can analyze the characteristics of early and late respondents to serve as a proxy for non-respondents, which helps identify any systematic differences that may influence the results (Armstrong & Overton, 1977). Moreover, examining the demographic composition of the respondents and comparing it with the known characteristics of the target population can provide insights into the sample's representativeness. The voluntary nature of participation, without any incentives, likely contributed to the low response rate. This is a recognized challenge in survey methodology, where the lack of immediate benefits for respondents often results in lower engagement (Dillman, Smyth, & Christian, 2014). Future research could consider employing incentives or alternative engagement strategies to improve response rates.

Power analysis for multiple regression typically suggests that a sample size of around 85 is adequate to detect medium effect sizes with a power of 0.80 and a significance level of 0.05 (Cohen, 1988). This means that with 85 participants, the study has an 80% chance of detecting a true effect if it exists, while maintaining a 5% risk of committing a Type I error (rejecting a true null hypothesis).

The sample size of 117 responses in this study exceeds this threshold, thus providing sufficient statistical power for the analysis. This larger sample size enhances the precision of the estimates and the robustness of the findings. It ensures that the study can reliably identify significant relationships between the UTAUT constructs (Performance Expectancy,

Effort Expectancy, Social Influence, Facilitating Conditions, Behavioral Intention, and Use Behavior) and demographic moderators (Gender, Age, Experience, Voluntariness of Use). Additionally, having a sample size that exceeds the recommended threshold helps to accommodate potential data quality issues such as outliers. This increases the reliability of the results and reduces the likelihood of Type II errors (failing to detect a true effect). Furthermore, a larger sample size improves the generalizability of the findings, allowing the results to be more confidently applied to the broader population (Field, 2018; Hair et al., 2010).

Overall, the adequate sample size of 117 responses strengthens the study's ability to provide meaningful insights and draw valid conclusions about the factors influencing the adoption of e-tendering applications among Greek companies.

3.3 Research instrument and measures

A research instrument is a critical tool closely tied to the research methodology, designed to collect, measure, and analyze data pertinent to the topic of interest. These instruments are foundational in ensuring that the data collected is relevant, accurate, and can be systematically analyzed to draw meaningful conclusions. Common examples of research instruments include questionnaires, interviews, surveys, observation forms, and aptitude tests. Each of these tools serves a unique purpose and is selected based on the specific needs of the research project.

Questionnaires are particularly popular in quantitative research for several reasons. They are among the most common, low-cost, quick, and efficient methods for gathering primary quantitative data from relatively large numbers of subjects. A questionnaire consists of a series of questions meticulously designed to elicit specific information from respondents. The structured nature of questionnaires allows for the systematic collection of data, which can then be easily quantified and analyzed statistically (Bryman, 2016).

Questionnaires can be broadly categorized into two types: self-administered and researcher-administered (Saunders et al., 2009). Self-administered questionnaires are those that respondents fill out on their own, typically through online platforms, mail, or paper forms. This method is highly convenient as it allows respondents to complete the survey at their own pace and convenience, potentially increasing the response rate and the honesty of the responses. Online surveys, in particular, have become increasingly popular due to their ease

of distribution and the ability to reach a wide audience quickly (Couper, 2008). On the other hand, researcher-administered questionnaires involve structured interviews conducted by the researcher. This method ensures that all questions are answered and allows the researcher to clarify any ambiguities in the questions, leading to more accurate and complete data collection. Structured interviews can be particularly useful in complex studies where the subject matter requires detailed explanations and interactions between the researcher and the respondent (Creswell, 2014). The choice between self-administered and researcher-administered questionnaires often depends on various factors, including the nature of the research question, the complexity of the survey, the target population, and the available resources. Self-administered questionnaires are advantageous for their efficiency and low cost, making them suitable for large-scale surveys. However, they may suffer from lower response rates and the risk of misunderstanding questions without the presence of an interviewer to provide clarification (Groves et al., 2009).

To develop the questionnaire for this study, a thorough review of relevant literature was conducted. The questionnaire was created using Google Forms, a cloud-based survey tool that allows for easy composition and distribution of form questions, as well as the collection of responses within the form or separately in Google Sheets for further analysis. Using Google Forms provided several advantages. Respondents could complete the survey at their convenience, enhancing the response rate and the reliability of the collected data. The questions were formulated in alignment with the Unified Theory of Acceptance and Use of Technology (UTAUT) to ensure that the resulting questionnaire was appropriately tailored for this study. This alignment helps investigate the attitudes and beliefs that underpin the behavior being studied. The initial draft of the questionnaire was shared with five participants for pre-testing. This pilot phase aimed to identify any ambiguous or difficult questions and other potential issues or inconsistencies. Feedback from the pre-test was used to make necessary adjustments to the wording and order of some questions, enhancing clarity and ensuring the questionnaire's effectiveness. The final version of the questionnaire, available in Appendices B and C of this dissertation, comprises 28 questions. These questions are organized according to the UTAUT constructs, facilitating the subsequent formulation of composite measures. The questionnaire included primarily close-ended questions with predefined response options. However, to capture more nuanced demographic data and account for responses that did not fit within the predefined categories, some questions featured an "Other" option, allowing respondents to provide additional

information. This semi-closed format retains the benefits of close-ended questions, such as ease of analysis, while also offering the flexibility to gather more detailed, qualitative data.

The questionnaire is divided into two main sections: Demographics and UTAUT Constructs. The Demographics section includes critical moderators for this study, such as Gender, Age, Experience, and Voluntariness of Use. It begins with eight demographic questions that provide essential background information about the respondents, followed by two questions focusing on experience and voluntariness of use. These demographic questions are crucial as they offer context for understanding response variability and help identify patterns that may influence technology adoption. Gender, Age, Experience, and Voluntariness of Use are significant moderators within the UTAUT model. The demographic section uses close-ended questions for the first nine items, with the tenth item (Voluntariness of Use) utilizing a 5-point Likert scale (1=strongly disagree, 5=strongly agree). The second section of the questionnaire assesses the core UTAUT constructs: Use Behavior, Behavioral Intention, Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions. These constructs are critical for understanding the factors that influence the adoption and use of e-tendering applications among professionals in the Greek private sector. Each of these constructs is evaluated through questions designed on a 5-point Likert scale (1=strongly disagree, 5=strongly agree), ensuring consistency and ease of analysis. A total of 18 questions are formulated under the UTAUT constructs section.

No negatively worded endpoints or random ordering of construct questions were included in the questionnaire for several key reasons. Negatively worded questions can confuse respondents, leading to misinterpretations and inconsistent responses, which compromise data reliability (Barnette, 2000). Keeping the questions consistently positive helps maintain respondent engagement and prevent cognitive fatigue, which can occur when switching between positive and negative phrasings, thus improving response quality (Swain, Weathers, & Niedrich, 2008). Additionally, positively framed questions are simpler to analyze and interpret, eliminating the need for score reversal and reducing errors during data interpretation (Podsakoff et al., 2003). Furthermore, avoiding random question ordering ensures a logical flow that facilitates better comprehension and more accurate responses. Random ordering can disrupt respondents' thought processes, resulting in fragmented answers that do not reflect their true opinions (Krosnick, 1991).

By structuring the questionnaire in this manner, the study ensures that the data collected is both relevant and manageable for statistical analysis, ultimately supporting the investigation of digital procurement solutions adoption.

3.3.1 Demographics

This section includes questions focused on key demographic factors such as gender, age, education level, position within the company, business unit, sector of operation, company size, and role in decision-making processes (Table 12). Additionally, this section includes questions that assess the respondents' experience with e-tendering applications (Table 13) and their voluntariness of use (Table 14).

The first question (Q1; DM1) addresses the respondent's gender, offering options for "Male" and "Female". This question helps to identify any gender-based differences in technology adoption, which is crucial for understanding how different genders may perceive and interact with e-tendering applications. Gender differences in technology adoption have been widely studied, and recognizing these differences can inform strategies to improve technology uptake across diverse groups (Venkatesh & Morris, 2000).

The second question (Q2; DM2) categorizes respondents by age, with options ranging from "24 years old or younger" to "65 years old or older." Age is a significant factor in technology adoption, as younger individuals often exhibit higher levels of comfort and familiarity with digital tools compared to older individuals (Morris & Venkatesh, 2000). By capturing a wide age range, the study can analyze how age-related factors influence the adoption and use of e-tendering applications.

The third question (Q3; DM3) inquires about the respondent's highest level of education, with options from "Primary - Lower Secondary Education Diploma" to "Doctoral Degree." Education level is a critical determinant of technology adoption, as individuals with higher educational attainment are generally more exposed to and proficient with digital technologies (Rogers, 2003). This question helps to correlate educational background with technology adoption behavior, providing insights into how educational differences may impact the use of e-tendering systems.

The fourth question (Q4; DM4) identifies the respondent's position within their company, ranging from "Owner" and "Senior Management (C-level, Director)" to "Middle Management," "Experienced Staff," and "Junior Staff." This question is important for

understanding how hierarchical position influences decision-making regarding technology adoption. Senior management and owners are likely to have a greater influence on strategic decisions, including the adoption of new technologies (Zhu, Kraemer, & Xu, 2006).

The fifth question (Q5; DM5) asks about the primary business unit in which the respondent works, with options such as "Procurement/Supply Chain," "Information Technology," "Administration," and "Human Resources." The business unit can significantly influence technology adoption, as different departments have varying needs and priorities regarding digital tools (Venkatesh et al., 2003). For example, IT professionals might have different perspectives compared to those in procurement or administration roles.

The sixth question (Q6; DM6) addresses the sector in which the respondent's company operates, including options like "Industry/Manufacturing," "Construction," "Hospitality/Food Service," "Retail Trade," "Transport/Logistics," "Telecommunications," "Energy," and "Financial." Sector-specific needs and norms can impact technology adoption rates, as some industries may have higher regulatory requirements or technological capabilities (Porter & Millar, 1985). For instance, industries with high regulatory requirements might prioritize e-tendering applications.

The seventh question (Q7; DM7) classifies the company size by the number of employees: "Under 50 employees," "51 to 250 employees," and "Over 250 employees." Company size can affect resource availability and the complexity of decision-making processes, with larger companies potentially having more resources to invest in new technologies (Thong & Yap, 1995). Also, smaller companies might prioritize different factors.

The eighth question (Q8; DM8) examines the respondent's role in the decision-making process for digital procurement solutions, with options such as "Lead Decision-Maker," "Decision Contributor," and "Not involved." This question provides insights into the level of influence respondents have over technology adoption, which can affect their responses to subsequent questions about e-tendering applications (Rogers, 2003). Also, lead decision-makers might have different perspectives compared to those who are not involved in the decision-making process.

Following the demographic questions, two items assess the respondents' experience with e-tendering applications and their voluntariness of use.

Experience with technology (Q9; EX1) is a key moderator in the UTAUT model, as familiarity with e-tendering applications can significantly influence adoption behavior

(Venkatesh et al., 2003). The question on experience with e-tendering applications provides options ranging from "No experience" to "More than 6 years," capturing a broad spectrum of familiarity levels. Those with more experience might have deeper insights into the benefits and challenges associated with these applications.

The voluntariness of use (Q10; VU1) is measured using a 5-point Likert scale (1=strongly disagree, 5=strongly agree). This item assesses the degree to which respondents feel they have the freedom to choose whether or not to use e-tendering applications. Voluntariness is a critical factor, as perceived autonomy can impact motivation and acceptance of new technologies (Deci & Ryan, 1985). If users feel they have the freedom to choose whether or not to use the applications, they might be more inclined to adopt them willingly.

3.3.2 UTAUT Constructs

This section is designed to measure six key constructs: Use Behavior (UB), Behavioral Intention (BI), Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC). Each construct is evaluated through three questions designed on a 5-point Likert scale (1=strongly disagree, 5=strongly agree).

Use Behavior (composite item: UB) is assessed with three questions (UB1, UB2, UB3) that measure the actual usage and integration of e-tendering applications into daily work routines (Table 15). For the overall UB score, the mean of the three items scores will be calculated. The questions are designed to capture how frequently and extensively respondents use e-tendering applications in their procurement activities. For instance, on question (Q11; UB1) asks respondents to indicate how regularly they use e-tendering applications in their procurement activities, while another (Q12; UB2) assesses the degree to which e-tendering applications are integrated into their daily work processes. The third question (Q13; UB3) examines the extent to which respondents utilize all available features of the e-tendering applications. These questions are crucial for determining the depth of technology adoption and understanding the practical application of e-tendering tools in the workplace (Venkatesh et al., 2003).

Behavioral Intention (composite item: BI) is measured through three questions (BI1, BI2, BI3) that evaluate the respondents' intentions to use e-tendering applications (Table 16). For the overall BI score, the mean of the three items scores will be calculated. One question (Q14; BI1) asks respondents about their intention of using e-tendering applications in their

future procurement activities. Another question (Q15; BI2) assesses whether respondents would recommend e-tendering applications to their peers, indicating their perceived value and satisfaction with the technology. The third question (Q16; BI3) predicts the frequency of future use, providing insights into the strength of respondents' commitment to adopting and using the technology. Behavioral intention is a strong predictor of actual use behavior and helps gauge the future trajectory of technology adoption (Ajzen, 1991).

Performance Expectancy (composite item: PE) involves three questions (PE1, PE2, PE3) that explore the perceived benefits of using e-tendering applications (Table 17). For the overall PE score, the mean of the three items scores will be calculated. These questions assess respondents' beliefs about how e-tendering can improve procurement efficiency, minimize errors, and enhance transparency. For example, one question (Q17; PE1) asks respondents if they believe that e-tendering applications would improve the efficiency of their procurement processes. Another question (Q18; PE2) evaluates whether respondents think that using e-tendering applications would help reduce errors in procurement activities. The third question (Q19; PE3) examines whether respondents perceive e-tendering applications as tools that enhance the transparency of procurement processes. Performance expectancy is a key determinant of behavioral intention and reflects the perceived usefulness of the technology (Davis, 1989).

Effort Expectancy (composite item: EE) is assessed through three questions (EE1, EE2, EE3) that measure the perceived ease of use and learning curve associated with e-tendering applications (Table 18). For the overall EE score, the mean of the three items scores will be calculated. These questions evaluate how easy respondents find it to use e-tendering applications and how much effort they believe is required to learn and maintain these systems. For instance, one question (Q20; EE1) asks respondents if they find e-tendering applications easy to use, while another (Q21; EE2) assesses whether they believe learning to operate an e-tendering application would be easy for them. The third question (Q22; EE3) examines respondents' perceptions of the effort required to maintain and update e-tendering applications. Effort expectancy influences behavioral intention, particularly among users who may have limited technical expertise (Venkatesh et al., 2003).

Social Influence (composite item: SI) is evaluated through three questions (SI1, SI2, SI3) that gauge the impact of social pressures from colleagues, business partners, and supervisors on the decision to use e-tendering applications (Table 19). For the overall SI score, the mean of the three items scores will be calculated. These questions examine how external

expectations and norms affect individual adoption behavior. For example, one question (Q23; SI1) asks whether people whose opinions respondents value think they should use e-tendering applications. Another question (Q24; SI2) assesses whether companies that respondents regularly do business with use e-tendering applications, highlighting the influence of industry standards. The third question (Q25; SI3) examines whether respondents' direct supervisors encourage them to use e-tendering applications. Social influence is a significant factor in technology adoption, especially in environments where usage is perceived as mandatory (Venkatesh & Davis, 2000).

Facilitating Conditions (composite item: FC) are measured through three questions (FC1, FC2, FC3) that assess whether the necessary technical, organizational, and infrastructural supports are available to use e-tendering applications effectively (Table 20). For the overall FC score the mean of the three items scores will be calculated. These questions evaluate the availability of resources, training, and financial support within the organization. For instance, one question (Q26; FC1) asks if respondents believe their company provides all necessary resources and technical support for using e-tendering applications. Another question (Q27; FC2) examines whether respondents feel well-trained and knowledgeable in using the applications. The third question (Q28; FC3) assesses whether the company allocates adequate financial resources to ensure the effective implementation and ongoing maintenance of e-tendering applications. Facilitating conditions directly affect use behavior by ensuring that users have the support they need to adopt and utilize the technology effectively (Venkatesh et al., 2003).

3.4 Statistical analysis

To analyze the collected quantitative data and identify significant predictors for the intention to adopt e-tendering applications, both Microsoft Excel (Microsoft 365; Microsoft Corp., USA) and the Statistical Package for the Social Sciences (SPSS version 21; IBM Corp., USA) were utilized. Initially, Excel was utilized to prepare and examine the dataset before conducting the main analysis in SPSS. In Excel, composite items were created and calculated, and a portion of the descriptive analysis was performed, to summarize the data and highlight trends.

Before conducting regression analysis in SPSS, categorical data were encoded using numeric encoding. This approach involved assigning unique numerical values to each

category, effectively preserving the ordinal nature of most categorical variables, such as education level, position within the company, size of the company, role in the decision-making process, and experience with e-tendering applications. Numeric encoding simplified the data structure and dataset, reducing the complexity associated with dummy coding, where multiple binary variables are created for each categorical variable. This simplification facilitated the inclusion of these variables in multiple regression models and made it easier to interpret the results of the analyses (Frost, 2019; Menard, 2010; Field, 2013). Additionally, responses initially categorized as "Other" that clearly fit into predefined categories were reclassified to improve data quality and consistency. This reclassification follows best practices in survey research methodologies, ensuring that the dataset is robust and reliable (Fowler, 2014; Groves et al., 2009; Dillman et al., 2014). By reclassifying "Other" responses, the analysis gains a more accurate representation of the data, enhancing the validity of the findings.

The above preparation was essential to ensure that the dataset was ready for advanced statistical analysis in SPSS, such as correlation and multiple regression analyses. By using both Excel and SPSS, the analysis was able to leverage the strengths of both tools. Excel's flexibility and ease of use for initial data preparation and descriptive analysis complemented SPSS's powerful statistical capabilities for more complex analyses. This approach ensured a comprehensive and rigorous analysis of the data, providing valuable insights into the factors influencing the adoption of e-tendering applications among professionals in the Greek private sector.

Chapter 4: Research Results

4.1 Reliability testing

Prior to any analysis, it is crucial to establish the reliability of each measure. This is achieved by evaluating their internal consistency using Cronbach's alpha, a widely recognized measure of reliability (Fornell & Larcker, 1981). Ensuring high reliability is essential for validating the composite items of the UTAUT model and providing confidence in the subsequent analysis (Venkatesh et al., 2003).

Reliability testing results confirm that the constructs used in this study possess good to excellent internal consistency, providing confidence in the accuracy and dependability of the data collected (table 1). The Use Behavior (UB) construct achieved an excellent Cronbach's alpha of 0.936, reflecting a high degree of consistency among the three items used to measure actual usage of e-tendering applications (table 22 & 23). Behavioral Intention (BI) also showed strong reliability, with a Cronbach's alpha of 0.868 (table 24 & 25). Performance Expectancy (PE), which measures the perceived benefits of using e-tendering applications, had a Cronbach's alpha of 0.875 (table 26 & 27). Effort Expectancy (EE) had a Cronbach's alpha of 0.704, meeting the acceptable threshold for reliability (table 28 & 29). This suggests that while the items are reasonably consistent in assessing the ease of use and learning associated with e-tendering applications, there may be room for refinement. The Social Influence (SI) construct, with a Cronbach's alpha of 0.789 (table 30 & 31), and Facilitating Conditions (FC), with a Cronbach's alpha of 0.773 (table 32 & 33), both demonstrated good internal consistency.

Constructs	Cronbach's alpha	Number of Items
Use Behavior (UB)	0.936	3
Behavioral Intention (BI)	0.868	3
Performance Expectancy (PE)	0.875	3
Effort Expectancy (EE)	0.704	3
Social Influence (SI)	0.789	3
Facilitating Conditions (FC)	0.773	3

Table 1. Cronbach's alpha values

4.2 Descriptive statistics

Descriptive analysis was conducted to outline the background characteristics and distribution (mean and standard deviation) of the survey sample. Table 21 in Appendix A presents the demographic profile of the 117 respondents who took part in this research.

Gender is a significant moderator in the UTAUT model (Venkatesh et al., 2003). Studies have shown that men and women may differ in their perceptions and usage of technology, with men often perceiving higher usefulness and ease of use, while women may be more influenced by social factors (Venkatesh & Morris, 2000). The dataset indicates that the majority of respondents are male, accounting for 55.6% of the sample, while female respondents make up 44.4% (figure 19 and table 21). This gender distribution may reflect the demographic composition of the industries surveyed or potential gender dynamics within decision-making roles related to e-tendering applications. Studies have shown that gender diversity can impact decision-making processes and organizational outcomes (Eagly & Carli, 2007). The slight male dominance in this sample aligns with the broader trends in certain industries where men traditionally occupy more roles in procurement and supply chain management (Peterson, 2017).

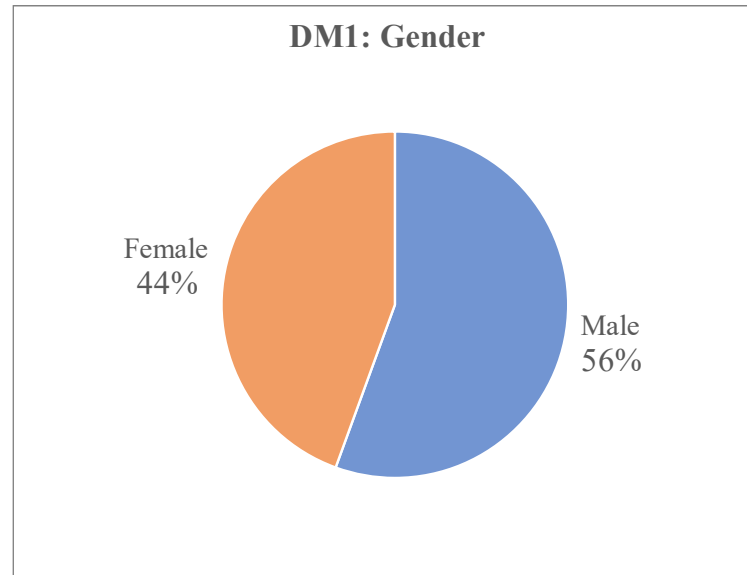


Figure 19. Distribution of respondents by gender

Age is another critical moderator in the UTAUT model, as it influences how users perceive and use technology. Older individuals may have different expectations and face more challenges in adopting new technologies compared to younger users (Venkatesh et al.,

2012). From the dataset we can see that most respondents fall within the age brackets of 35 to 44 years old (33.3%) and 45 to 54 years old (30.8%).

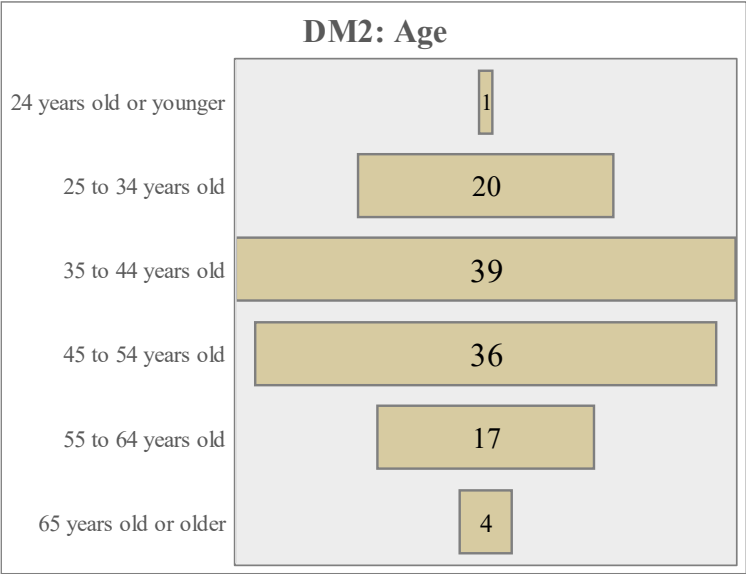


Figure 20. Distribution of respondents by age

This concentration in the mid-career age ranges suggests that individuals in these age groups are more likely to be involved in decision-making processes related to e-tendering applications. A smaller percentage of respondents are 34 years old or younger (17.9%) and 55 years old or older (17.9%) indicating that younger and older individuals are less represented. This age distribution highlights the importance of designing user-friendly systems that cater to different age groups. Figure 20 and table 21.

The highest frequency of respondents holds a Master’s Degree (49.6%), followed by those with a Higher Education Degree (35.0%). This high level of educational attainment suggests that decision-makers in the context of e-tendering applications are typically well-educated, which may influence their perceptions and acceptance of technological solutions. Higher education levels are often associated with greater openness to innovation and technology adoption (Rogers, 2003). Individuals with advanced degrees may possess a better understanding of the benefits and functionalities of e-tendering systems, leading to higher engagement and utilization. Additionally, higher education enhances problem-solving skills and the capacity to manage complex systems, crucial for effective e-tendering implementation. Figure 21 and Table 21 illustrate this distribution, underscoring the importance of education in shaping e-tendering adoption.

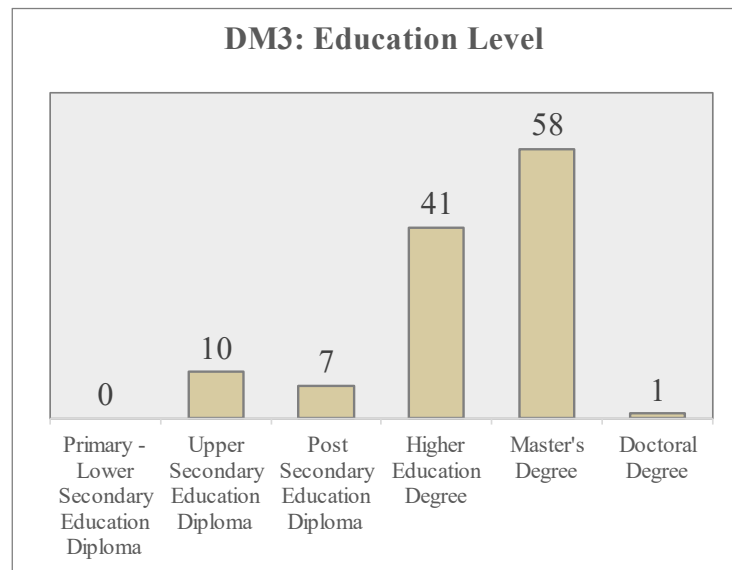


Figure 21. Distribution of respondents by education level

Most respondents are Experienced Staff (33.3%) and Middle Management (29.1%). This distribution highlights that mid-level employees and those with substantial experience play a significant role in the decision-making processes for e-tendering applications. Senior Management (23.1%) and Owners (11.1%) are also represented, indicating a diverse range of job roles involved in the survey. The involvement of various hierarchical levels underscores the importance of comprehensive engagement across an organization for successful technology adoption (Davis, 1989). Figure 22 and table 21.

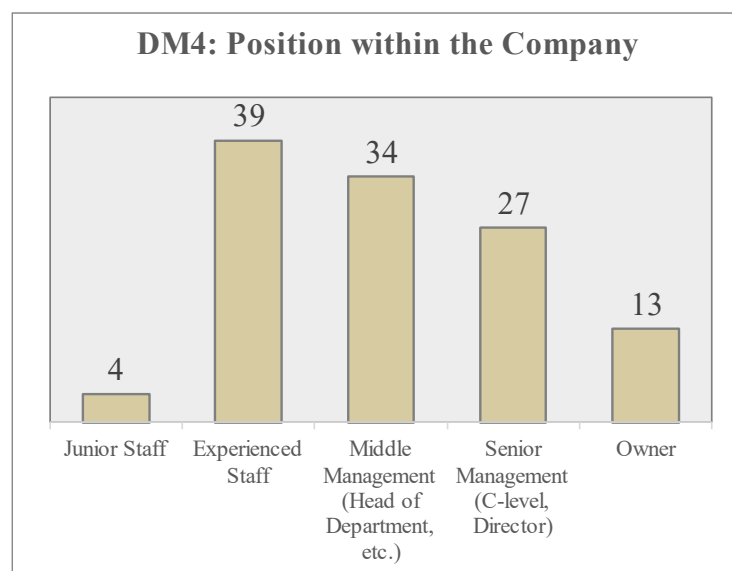


Figure 22. Distribution of respondents by position within the company

A significant portion of the respondents (43.6%) work in the Procurement/Supply Chain business unit, directly relevant to e-tendering applications. The Administration business unit also has a substantial representation (29.1%), indicating that administrative roles are heavily involved in the processes surrounding e-tendering applications. Information Technology (IT) is represented by 6.0% of respondents, highlighting the technical support required for these applications. Additionally, 6.0% of respondents are from Commercial/Sales and Financial/Accounting units, respectively. Human Resources (2.6%) and other business units (6.8%) make up the rest of the sample, demonstrating the interdisciplinary nature of e-tendering processes (Monczka et al., 2015; Davila, Gupta, & Palmer, 2003; Gunasekaran, McGaughey, & Ngai, 2009; Croom & Brandon-Jones, 2007). Figure 23 and table 21.

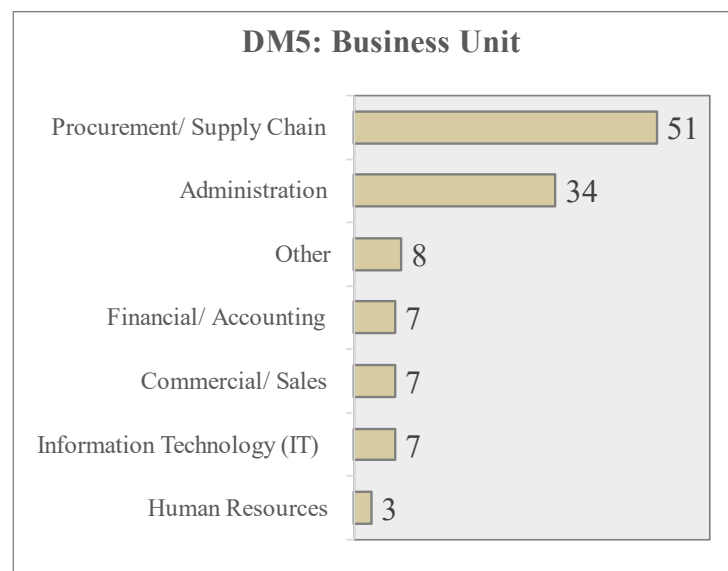


Figure 23. Distribution of respondents by business unit within the company

The respondents come from a variety of sectors, with Industry/Manufacturing being the most frequent (21.4%). Other sectors such as Construction (10.3%), Energy (10.3%), and Health/Medical (7.7%) are also represented. This diversity indicates that e-tendering applications are of interest across a wide range of industries, each with its unique requirements and challenges. The involvement of diverse sectors underscores the versatility and applicability of e-tendering solutions, reflecting a broad recognition of their benefits in improving procurement efficiency and transparency. Moreover, it highlights the potential for cross-industry learning and collaboration in optimizing e-tendering processes. Figure 24 and Table 21 provide a clear illustration of this sectoral distribution, emphasizing the widespread relevance and adoption of e-tendering applications across different industries.

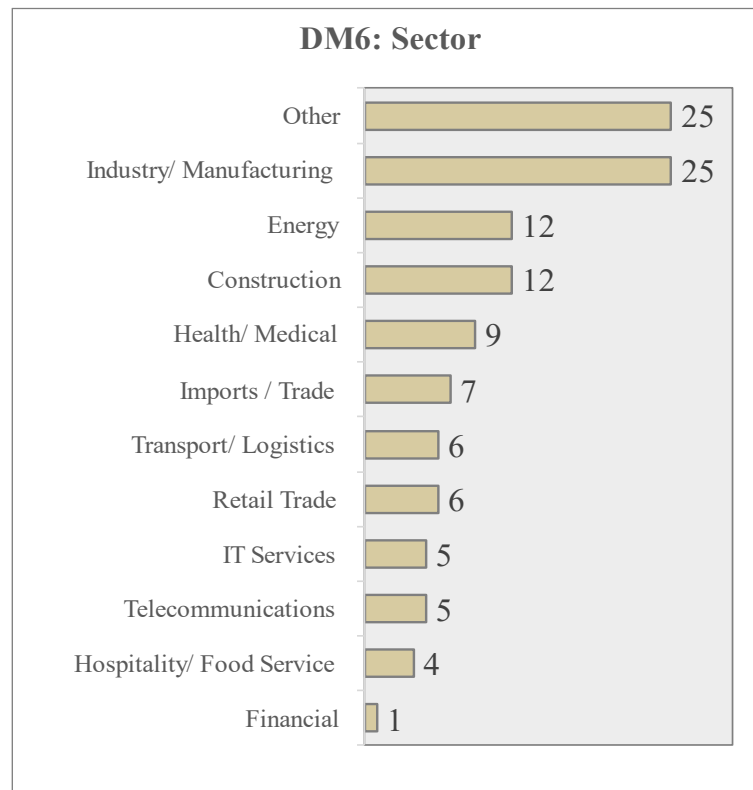


Figure 24. Distribution of respondents by the sector in which the company operates

The majority of respondents are from companies with under 50 employees (46.2%), followed by those from companies with over 250 employees (33.3%). This distribution suggests that both small and large enterprises are engaged with e-tendering processes, but there may be varying levels of resource availability and technological adoption between these groups. Smaller companies, which constitute a significant portion of the sample, might face unique challenges compared to their larger counterparts. These challenges can include limited financial resources, fewer technical staff, and less formalized procurement processes. Such constraints can impact their ability to invest in and effectively utilize advanced procurement technologies (Premkumar, 2003). Conversely, larger companies, often have more resources at their disposal. These resources can include dedicated procurement departments, advanced IT infrastructure, and greater financial capacity to invest in sophisticated e-tendering solutions. Larger companies are likely to leverage these resources to fully integrate e-tendering systems into their procurement processes, thereby achieving greater efficiency and compliance. Figure 25 and table 21.

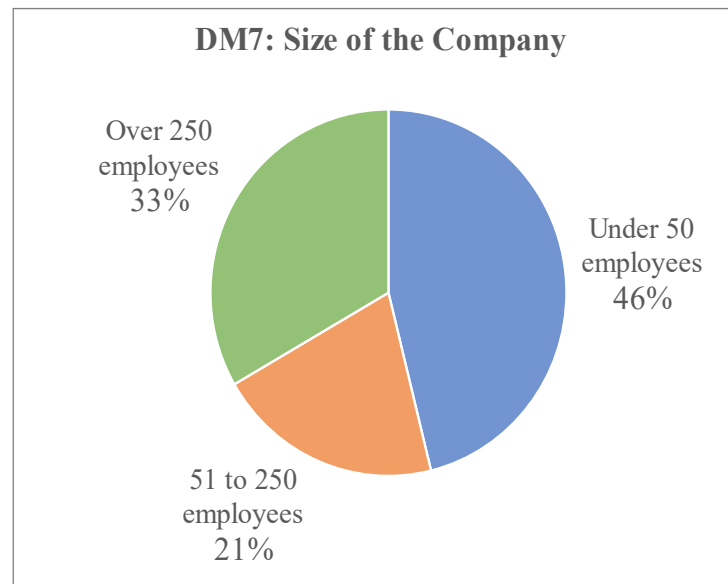


Figure 25. Distribution of respondents by the size of the company

The most common role in the decision-making process for digital procurement solutions is that of a Decision Contributor (52.1%). Lead Decision-Makers (25.6%) and those Not Involved (22.2%) are also present. This indicates that a collaborative decision-making approach is prevalent, with input from multiple stakeholders within the organization. Collaborative decision-making processes are essential for the successful implementation and acceptance of new technologies (Karahanna, Straub, & Chervany, 1999). Figure 26 and table 21.

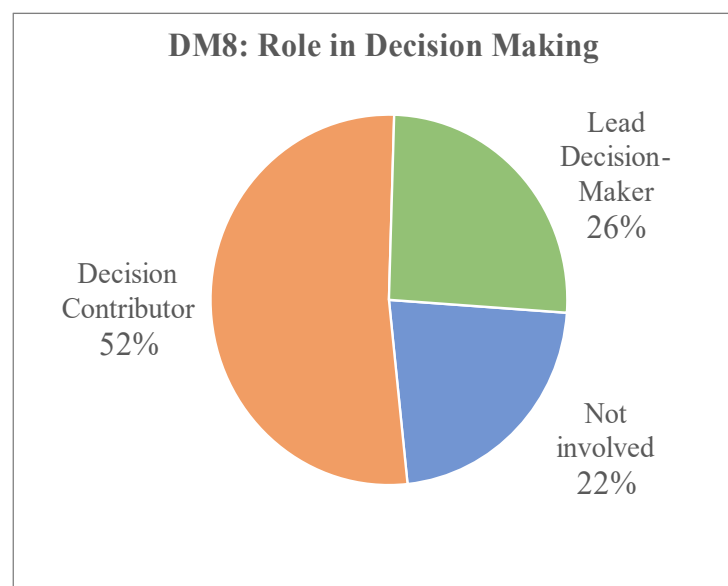


Figure 26. Distribution of respondents by role in decision-making

Experience with technology is a significant moderator in the UTAUT model, as more experienced users are generally more comfortable and proficient with new technologies (Venkatesh et al., 2003). A substantial number of respondents (40.2%) have more than 6 years of experience with e-tendering applications (figure 27 and table 21). This high level of experience may influence their perceptions and attitudes towards these applications, potentially leading to more informed and favorable views on their implementation and use. Additionally, 21.4% have no experience, indicating a significant segment of potential new adopters who may require more support and training. Experience with technology plays a critical role in its acceptance and effective use (Agarwal & Prasad, 1999).

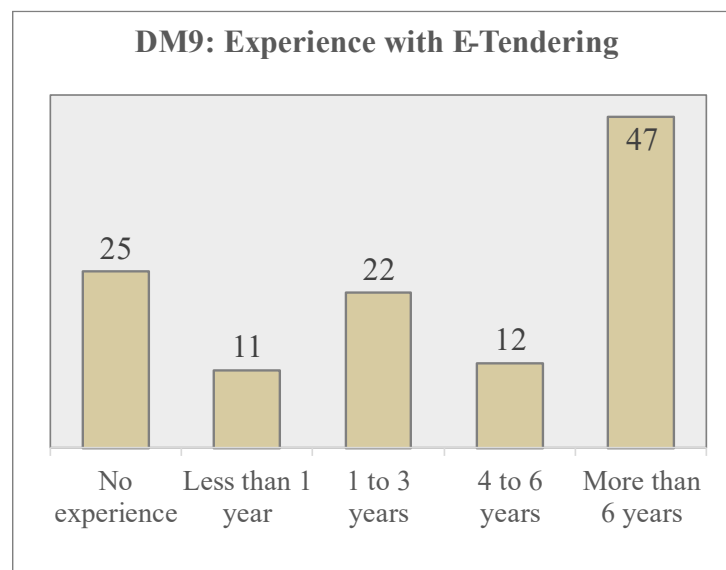


Figure 27. Distribution of respondents by experience with e-tendering applications

In the UTAUT model, voluntariness of use (VU) is an important moderator that influences the relationship between social influence and behavioral intention, particularly distinguishing contexts where technology use is mandatory versus voluntary. (Venkatesh et al., 2003). Voluntariness of Use was measured by a single item (VU1), which assessed the degree of freedom respondents felt they had in deciding whether or not to use e-tendering applications. The mean score for VU1 was 3.03, with a standard deviation of 1.423 (figure 28 and table 21). This mean score suggests a moderate level of perceived voluntariness among respondents, indicating that while some degree of organizational pressure or expectations might exist, many respondents still feel they have a personal choice in using these applications.

The standard deviation of 1.423 is relatively high, indicating substantial variation in responses. This suggests that respondents may have had diverse perceptions of their freedom to choose whether or not to use e-tendering applications. Such variability can be attributed to differences in organizational policies, individual roles, and subjective interpretations of the VU1 question. The diversity in responses could stem from various organizational contexts where the concept of "freedom to choose" might differ significantly. In some organizations, the use of e-tendering applications might be strictly enforced, while in others, it could be more of a recommendation or optional practice. Additionally, the subjective nature of perceived voluntariness means that some respondents may feel they have autonomy despite organizational expectations, while others may feel compelled to use the technology regardless of actual freedom. This variability can be also understood through Ajzen's (1991) and Gagne & Godin's (2000) insights, which suggest that belief-based items, such as perceived voluntariness, require more reasoned responses. This leads to diverse interpretations and greater variability in responses as individuals reflect deeply on their autonomy beliefs.

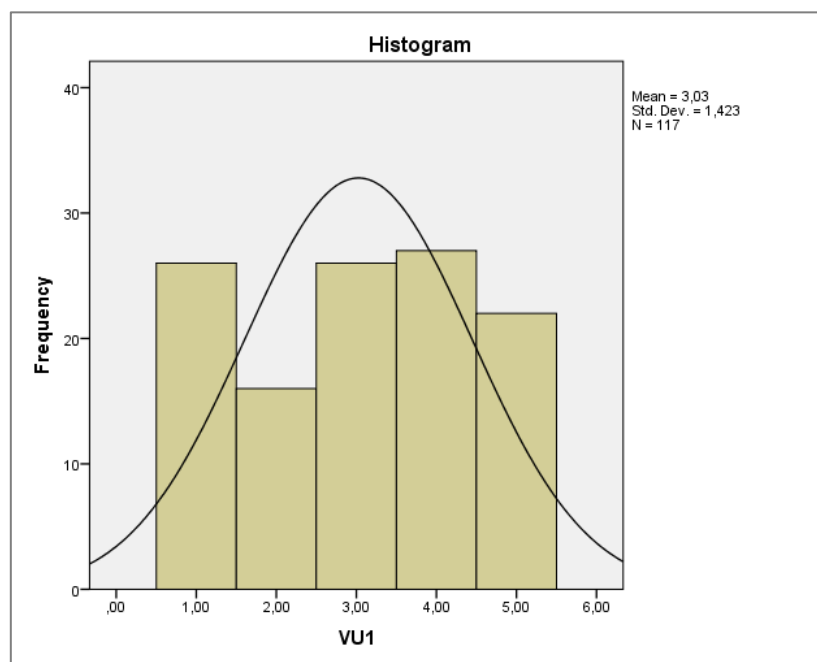


Figure 28. Frequency distribution of Voluntariness of Use

For the above item and the following composite items UB, BI, PE, EE, SI and FC, which were measured using a Likert scale, frequency distributions were calculated in SPSS. Calculating frequency distributions is a fundamental step in understanding the distribution of responses and identifying any potential patterns or anomalies in the data (De Vaus, 2013).

Use Behavior (UB) is assessed using three items (UB1, UB2, UB3), which measure the actual use and integration of e-tendering applications in daily work. The histogram for the Use Behavior (UB) composite item below reveals important insights into the respondents' use of e-tendering applications. The mean score is 3.06, with a standard deviation of 1.389, based on a sample of 117 respondents (figure 29). This mean score indicates a moderate level of use behavior among the respondents. The histogram shows a wide spread of responses across the scale, indicating that respondents have varied levels of engagement with e-tendering applications. The substantial standard deviation (1.389) further supports the observation that there is considerable variability in the respondents' use behavior. This variability could be influenced by factors such as differences in organizational policies, individual roles, levels of experience with e-tendering, and the perceived usefulness and ease of use of the applications.

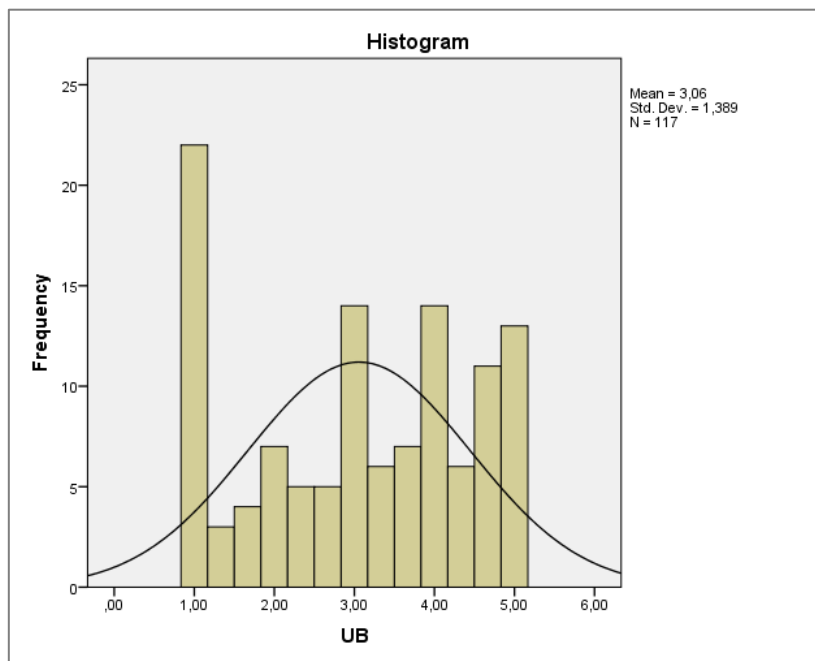


Figure 29. Frequency distribution of the composite item of Use Behavior

The distribution in the histogram highlights noticeable peaks at both the lower end (around 1) and the upper end (around 5) of the scale. This pattern suggests that while a significant portion of respondents rarely use e-tendering applications, a similar portion are frequent users. This bimodal distribution points to the critical role of experience in the actual use of e-tendering applications. To further investigate this, a bivariate correlation analysis was conducted in SPSS between UB (Use Behavior) and EX1 (experience with e-tendering applications). The analysis (Table 2) shows a strong positive relationship, with a Pearson

correlation coefficient of 0.630. This indicates that higher levels of experience with e-tendering applications are associated with higher use behavior. The p-value of 0.000, confirms that this correlation is statistically significant at the 0.01 level. This finding is consistent with the theoretical framework suggesting that increased familiarity and comfort with technology lead to higher usage levels (Venkatesh et al., 2003). Further analysis could explore how other factors, such as facilitating conditions and effort expectancy, interact with experience to influence use behavior.

Behavioral Intention (BI) is measured using three items (BI1, BI2, BI3), which capture the respondents' intention to use e-tendering applications in the future. The composite mean and standard deviation suggest that respondents have a strong intention to use e-tendering applications in their future procurement activities (Mean=3.76, Std. Deviation=0.994). The distribution below (figure 30) also shows a positive skew, with a higher concentration of scores towards the upper end of the scale. Further analysis will explore correlations between BI and other UTAUT constructs to better understand the factors driving these intentions.

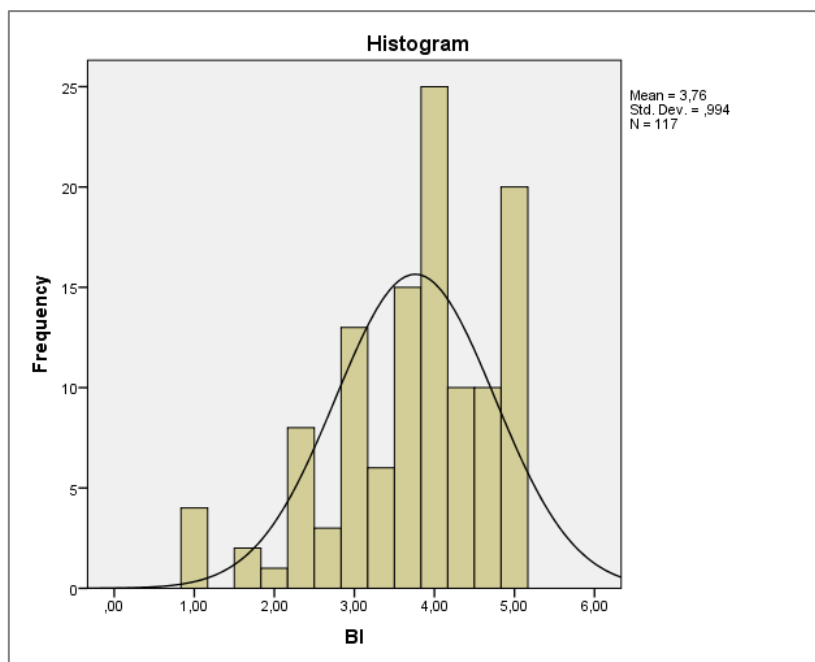


Figure 30. Frequency distribution of the composite item of Behavioral Intention

Performance Expectancy (PE) is assessed using three items (PE1, PE2, PE3), which measure the perceived benefits of using e-tendering applications in terms of improving efficiency, minimizing errors, and enhancing transparency in procurement processes. The

composite mean of 3.91 and standard deviation of 0.885 indicate that respondents generally agree that e-tendering applications will positively impact their job performance (figure 31).

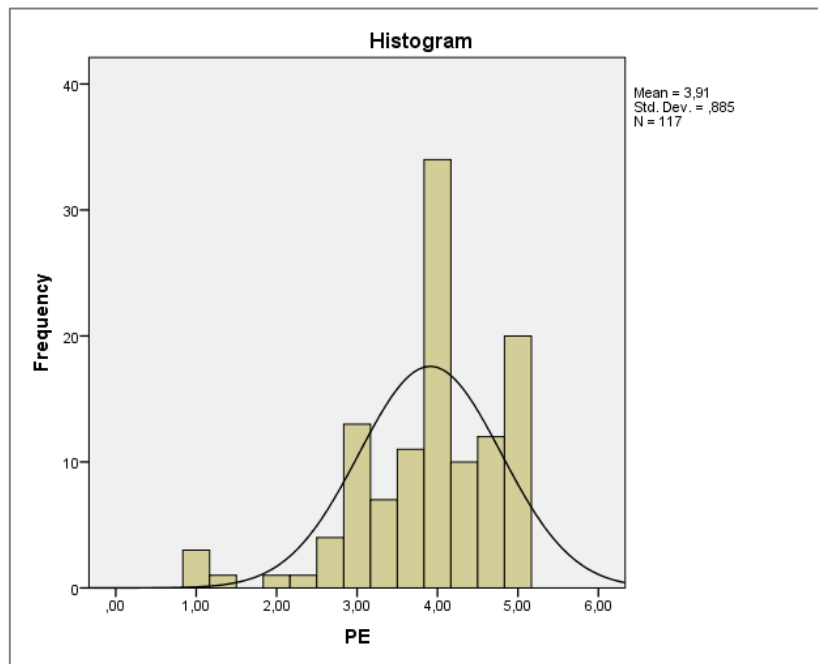


Figure 31. Frequency distribution of the composite item of Performance Expectancy

The histogram above shows a concentration of scores around 4, indicating that while most respondents perceive high performance expectancy, there are still some who are less convinced about the benefits. This distribution suggests that while e-tendering applications are largely seen as beneficial, there is room for increasing awareness and understanding of their advantages among all users. The variability in responses highlights that, although the general perception is positive, there remains a segment of respondents who are less certain about the advantages of e-tendering applications. It suggests that while many users recognize the potential for these systems to improve procurement processes, further efforts may be needed to fully convince all users of their effectiveness.

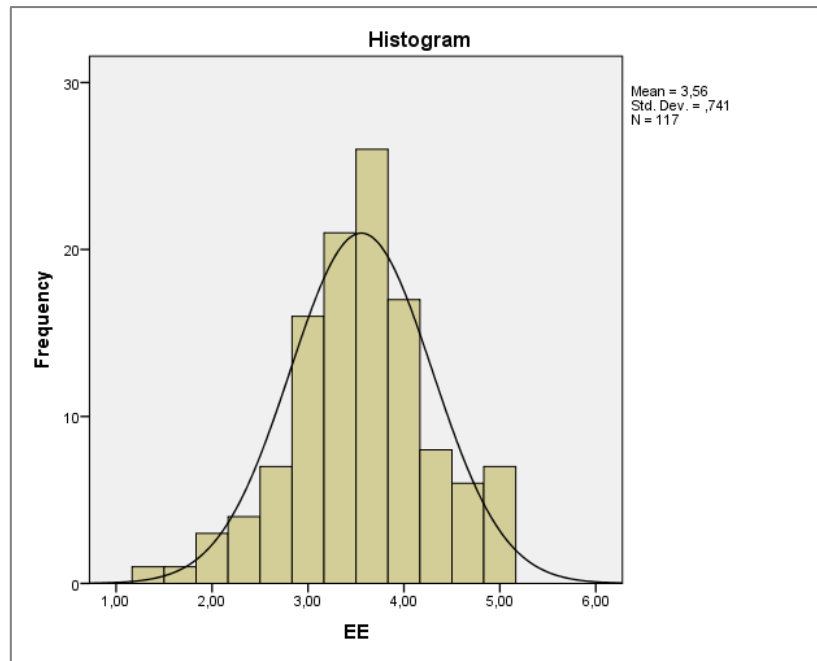


Figure 32. Frequency distribution of the composite item of Effort Expectancy

Effort Expectancy (EE) is captured through three items (EE1, EE2, EE3), which assess the ease of use and learning associated with e-tendering applications. The composite mean of 3.56 and standard deviation of 0.741 reflect that respondents generally find e-tendering applications moderately easy to use and learn (figure 32).

Social Influence (SI) is measured using three items (SI1, SI2, SI3), which evaluate the impact of important others and peer pressure on the intention to use e-tendering applications. The composite mean and standard deviation suggest that social influence has a moderate impact on the respondents' intention to use e-tendering applications. The distribution is approximately normal, with a peak around the score of 3, suggesting that the majority of respondents neither strongly agree nor strongly disagree about experiencing social influence to use the technology (figure 33). This indicates that while some respondents feel a certain level of peer pressure or encouragement from colleagues to use e-tendering applications, it is not a predominant factor influencing their decision. Furthermore, the moderate impact of social influence might imply that individual attitudes towards e-tendering are more significantly shaped by personal perceptions of the technology's utility and ease of use rather than by external social pressures.

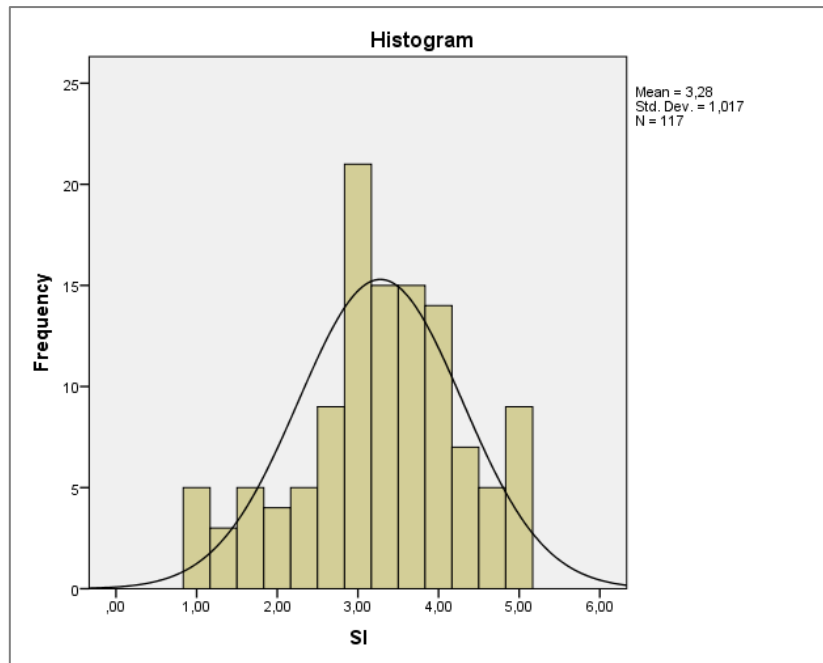


Figure 33. Frequency distribution of the composite item of Social Influence

Facilitating Conditions (FC) are assessed using three items (FC1, FC2, FC3), which measure the availability of resources and support for using e-tendering applications. The mean score is 3.52, with a standard deviation of 1.029 (figure 34). This mean score indicates a moderate level of perceived facilitating conditions among respondents. Also, the histogram displays a roughly normal distribution with a peak around the score of 3, indicating that the majority of respondents have an average perception of the facilitating conditions.

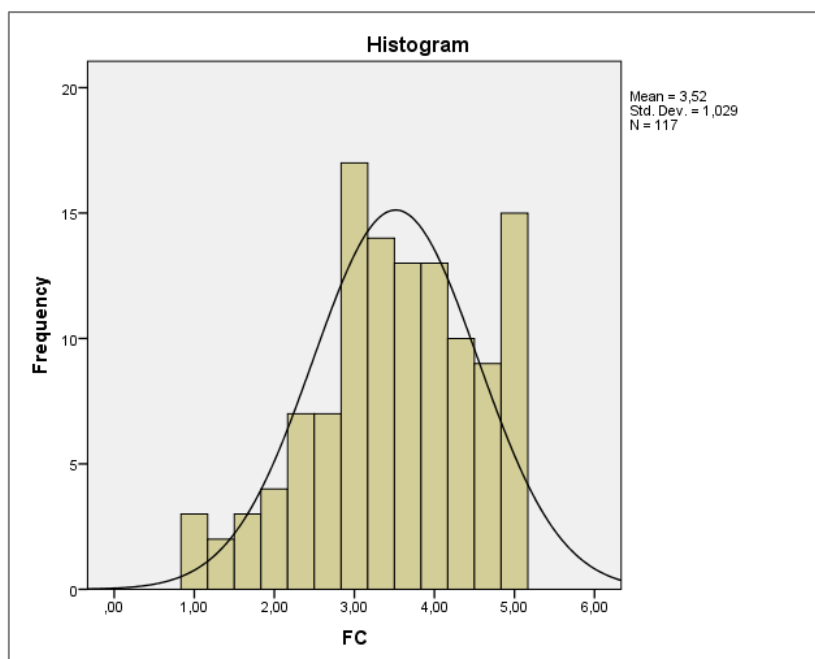


Figure 34. Frequency distribution of the composite item of Facilitating Conditions

The above descriptive statistics for the UTAUT constructs, including composite means and standard deviations, provide a comprehensive overview of respondents' perceptions and behaviors related to e-tendering applications. High scores in Performance Expectancy and Behavioral Intention indicate strong positive perceptions and intentions towards using these applications. Effort Expectancy and Facilitating Conditions also show favorable responses, suggesting that respondents find the applications easy to use and feel supported by their organizations. Social Influence, while moderate, indicates that peer and organizational pressures do play a role in influencing technology adoption. Overall, the data indicate generally positive perceptions and intentions toward e-tendering applications, with moderate to high variability in responses.

4.3 Correlation and regression analysis

The scope of the analysis is to explore and understand the relationships between the core constructs of the UTAUT model, as well as to examine the impact of demographic moderators on these relationships. This analysis is divided into three main parts, with additional steps to incorporate hierarchical regression for examining the impact of moderators.

The first part involves conducting a correlation analysis to assess the relationships between the primary UTAUT constructs: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Behavioral Intention (BI), and Use Behavior (UB). Additionally, this part will include examining correlations with demographic moderators such as Gender (DM1), Age (DM2), Experience (EX1), and Voluntariness of Use (VU1). This will provide a preliminary understanding of how these constructs and demographic factors are interrelated (Venkatesh et al., 2003; Ajzen, 1991).

The second part focuses on multiple linear regression analysis for Behavioral Intention (BI), combined with hierarchical regressions to incorporate demographic moderators. Specifically, we will analyze how Performance Expectancy (PE), Effort Expectancy (EE), and Social Influence (SI) affect Behavioral Intention (BI), and then explore how the inclusion of interaction terms with demographic moderators (Gender, Age, Experience, Voluntariness of Use) influence these relationships (Field, 2013).

The third part of the analysis extends to predicting Use Behavior (UB) by examining, with the use of multiple linear regression analysis, the effects of Behavioral Intention (BI) and Facilitating Conditions (FC) on Use Behavior (UB). This part will also include hierarchical regressions to explore the moderating effects of demographic variables (Age, Experience).

Multiple linear regression is a statistical technique that models the relationship between one dependent variable and two or more independent variables. This approach allows for the examination of the effect of each independent variable while controlling for the others. This is crucial in the UTAUT model as it helps in understanding the unique contribution of each construct (PE, EE, SI, FC) to Behavioral Intention and Use Behavior (Hair et al., 2010; Cohen et al., 2003).

For the outcomes of these analyses, a p-value of less than 0.05 will be considered statistically significant. This threshold indicates that there is less than a 5% probability that the observed relationships occurred by chance, thereby providing confidence in the robustness of the findings. The p-value represents the probability that the observed data would occur if the null hypothesis were true. It quantifies the strength of evidence against the null hypothesis. In his book "Statistical Methods for Research Workers," Ronald A. Fisher introduced the concept of the p-value and proposed the 0.05 threshold as a criterion for statistical significance. This threshold has since become a standard in hypothesis testing (Fisher, 1925).

4.3.1 Correlation Analysis

The Pearson correlation coefficient was used (Table 2). Pearson correlation is a statistical measure that evaluates the strength and direction of the linear relationship between two continuous variables. The correlation coefficient, denoted by r , ranges from -1 to 1. A positive correlation implies that as one variable increases, the other variable also increases, while a negative correlation implies that as one variable increases, the other decreases. The significance of the correlation is assessed using a p-value, with a threshold set at $p < 0.05$.

There is a strong positive correlation between Performance Expectancy (PE) and Behavioral Intention (BI) ($r = 0.663$, $p < 0.01$). This suggests that individuals who perceive higher benefits and performance improvements from using e-tendering applications are more likely to intend to use them. Effort Expectancy (EE) shows a moderate positive correlation with BI ($r = 0.333$, $p < 0.01$), indicating that the easier the application is to use, the more likely users are to intend to use it. Social Influence (SI) is strongly positively correlated with BI ($r = 0.619$, $p < 0.01$), highlighting that social factors, such as the influence of colleagues and superiors, play a crucial role in shaping individuals' intentions to use e-tendering applications. There are also strong positive correlations of PE, EE and SI with UB.

Facilitating Conditions (FC) has a strong positive correlation with Behavioral Intention (BI) ($r = 0.550$, $p < 0.01$) and Use Behavior (UB) ($r = 0.678$, $p < 0.01$). This indicates that when users have access to the necessary resources and support to use e-tendering applications, their actual usage increases. There is also a strong positive correlation between BI and UB ($r = 0.634$, $p < 0.01$), demonstrating that individuals who intend to use e-tendering

applications are more likely to actually use them. This relationship underscores the predictive power of behavioral intention within the UTAUT model.

Experience (EX1) is strongly positively correlated with UB ($r = 0.630, p < 0.01$), as we have seen previously, suggesting that greater experience with e-tendering applications is associated with higher use behavior. Experience also shows a moderate positive correlation with BI ($r = 0.324, p < 0.01$), indicating that experience positively influences behavioral intention. Voluntariness of Use (VU1) is not significantly correlated with BI ($r = 0.031, p > 0.05$) or UB ($r = -0.044, p > 0.05$), indicating that perceived voluntariness does not have a strong influence on behavioral intention or use behavior in this context.

Gender (DM1) did not show significant correlations with BI or UB, suggesting that gender may not be a determining factor in the intention or actual use of e-tendering applications in this context. Age (DM2) has a weak positive correlation with UB ($r = 0.225, p < 0.05$).

Regarding the rest of the demographics, Education Level (DM3) and Position within the Company (DM4) did not show significant correlations with BI or UB. Business Unit within the Company (DM5), also did not show significant correlations with BI or UB, suggesting that the specific business unit might not significantly influence the intention or use of e-tendering applications. Similarly, the Sector in which the Company operates (DM6) did not show significant correlations with BI or UB, indicating that the industry sector may not play a critical role. Size of the Company (DM7) and Role in Decision-Making Process (DM8) did not show a significant correlation with BI and UB.

Correlations																
	DM1	DM2	DM3	DM4	DM5	DM6	DM7	DM8	EX1	VU1	UB	BI	PE	EE	SI	FC
DM1	1															
DM2	-,140	1														
DM3	-,180	-,173	1													
DM4	-,188*	,456**	-,084	1												
DM5	,085	,059	-,093	,072	1											
DM6	,012	,239**	-,055	,163	,170	1										
DM7	-,162	-,148	,181	-,328**	-,092	-,131	1									
DM8	-,318**	,347**	-,055	,588**	-,102	,083	-,147	1								
EX1	-,065	,374**	-,074	,226*	,003	,202*	-,050	,410**	1							
VU1	-,065	,116	-,110	,259**	-,083	,025	-,073	,392**	,034	1						
UB	,038	,225*	-,064	-,042	-,032	,090	,097	,129	,630**	-,044	1					
BI	,100	,119	-,051	-,123	-,058	,074	,164	-,009	,324**	,031	,634**	1				
PE	,132	,098	-,049	-,074	,009	,166	,165	-,093	,172	-,085	,427**	,663**	1			
EE	,065	-,090	-,054	-,101	-,220*	-,021	,241**	,019	,044	,076	,271**	,333**	,447**	1		
SI	,144	,068	-,081	-,195*	,065	,030	,152	-,034	,297**	-,033	,669**	,619**	,601**	,331**	1	
FC	-,047	,204*	-,091	,067	,072	,208*	,161	,213*	,569**	-,017	,678**	,550**	,522**	,358**	,541**	1

*. Correlation is significant at the 0.05 level (2-tailed).

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

Table 2. Pearson's correlation coefficient matrix (Source: SPSS)

4.3.2 Regression Analysis for Behavioral Intention

Regression analysis is a powerful statistical method used to examine the relationships between dependent and independent variables. Within the framework of the Unified Theory of Acceptance and Use of Technology (UTAUT), this technique is important in understanding how various factors influence users' behavioral intentions to adopt technology. In this study, regression analysis enables us to evaluate the direct effects of Performance Expectancy (PE), Effort Expectancy (EE), and Social Influence (SI) on Behavioral Intention (BI), and to investigate the moderating effects of the demographic variables Gender (DM1), Age (DM2), Experience (EX1), and Voluntariness of Use (VU1).

The analysis begins with an initial multiple linear regression to understand the direct effects of PE, EE, and SI on BI. This step provides a baseline understanding of how these key constructs influence users' intentions to use e-tendering applications. To ensure accurate interpretation and to mitigate multicollinearity issues, also in the next steps, it is essential to standardize all items in the model by transforming them into Z-scores. This standardization will help in neutralizing scale differences between key constructs and moderators, allowing for a more accurate interpretation of coefficients, particularly when comparing the strength of different predictors.

The predictors entered into the regression model in SPSS include Social Influence (SI), Effort Expectancy (EE), and Performance Expectancy (PE), with no variables removed. The correlation coefficient (R) of 0.718 indicates a strong positive relationship between the predictors and Behavioral Intention (BI). The R^2 value of 0.516 suggests that approximately 51.6% of the variance in BI is explained by the model, indicating substantial explanatory power (table 3 & 34). The adjusted R^2 value of 0.503 accounts for the number of predictors in the model and confirms the model's strength after adjustment. The ANOVA results show that the regression model is statistically significant, with an F-statistic of 40.179 and a p-value of 0.000, indicating that the observed relationships are unlikely to have occurred by chance (table 35). The standardized coefficients (table 36) indicate that Performance Expectancy (PE) has the strongest positive effect on BI, with a Beta of 0.449, meaning a one standard deviation increase in PE results in a 0.449 standard deviation increase in BI. Social Influence (SI) also shows a substantial positive effect on BI, with a Beta of 0.343. Effort Expectancy (EE), however, has a negligible effect on BI, with a Beta of 0.018. The t-statistics and their associated p-values indicate that PE and SI are statistically significant predictors of BI (p-values of 0.000), while EE is not (p-value of 0.803).

Overall, the initial regression analysis reveals that Performance Expectancy (PE) and Social Influence (SI) are significant predictors of Behavioral Intention (BI), both showing strong positive effects, while Effort Expectancy (EE) does not significantly predict BI in this model (figure 35). The model explains a significant portion of the variance in BI. These findings suggest that users' expectations of performance and social influences play a critical role in their intention to use e-tendering applications, while the ease of use (Effort Expectancy) does not have a significant impact in this context. This aligns with the UTAUT framework, highlighting the importance of perceived usefulness and social factors in technology adoption.

	R²	F	Beta	Sig.
BI (Behavioral Intention, Dependent Variable)	0.516	40.179, p=0.000		
PE (Performance Expectancy, Predictor)			0.449	0.000
EE (Effort Expectancy, Predictor)			0.018	0.803
SI (Social Influence, Predictor)			0.343	0.000

Table 3. Summary table of the multiple regression analysis for Behavioral Intention

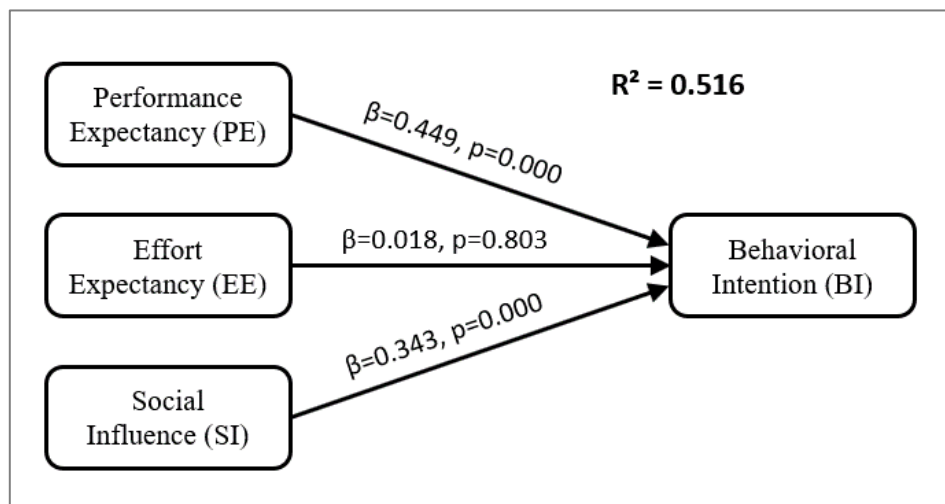


Figure 35. Results of multiple regression analysis in which Behavioral Intention was regressed on Performance Expectancy (PE), Effort Expectancy (EE) and Social Influence (SI).

Having determined the direct effects, we proceed to hierarchical regression analyses to assess the moderating effects of demographic variables. Hierarchical regression analysis is particularly useful for testing the influence of additional variables (in this case, demographic variables) on a model already containing main effect terms. By incorporating interaction terms, it allows for the evaluation of how the relationships between main predictors (PE, EE, SI) and the outcome (BI) change when considering demographic variables. Interaction terms are the products of moderators and predictors, which are created by multiplying the relevant z score variants of independent variables and moderators. For the moderated regression analysis, whenever an interaction term is included, also the two variables from which the term was derived, are included. For the hierarchical analysis, the process begins by including the direct effects of PE, EE, and SI, followed by the inclusion of the moderator and the interaction terms.

To examine the moderating effect of Gender we introduce three interaction terms into the model: DM1xPE, DM1xEE, DM1xSI. This allows us to determine how gender influences the relationship between the UTAUT constructs and BI. The inclusion of these interaction terms (table 4, 37 & 38) resulted in only a marginal increase in R^2 from 0.516 to 0.518, and the change in R^2 was not statistically significant (F Change = 0.108, p = 0.980). This indicates that the interaction terms did not significantly improve the explanatory power of the model. Further examination of the coefficients for the interaction terms (table 39) revealed that none of them were significant. Specifically, the interaction terms DM1xPE (Beta = 0.005, p = 0.953), DM1xEE (Beta = 0.044, p = 0.558), and DM1xSI (Beta = -0.020, p = 0.826) all showed p -values well above the 0.05 threshold, indicating that gender does not significantly moderate the relationships between PE, EE, SI, and BI.

These findings suggest that while performance expectancy and social influence are important determinants of behavioral intention, gender does not play a significant moderating role in these relationships within the context of e-tendering application adoption. This outcome implies that the influence of perceived performance and social factors on the intention to use technology is consistent across different genders. Consequently, gender does not alter the strength or direction of these relationships, reinforcing the direct effects of PE and SI on BI as posited by the UTAUT model (figure 36).

	R²	F	Beta	Sig.
BI (Behavioral Intention, Dependent Variable)	0.518	16.737, p=0.000		
PE (Performance Expectancy, Predictor)			0.459	0.000
EE (Effort Expectancy, Predictor)			0.010	0.897
SI (Social Influence, Predictor)			0.346	0.000
DM1 (Gender, Predictor)			-0.011	0.874
DM1xPE (Interaction Term)			0.005	0.953
DM1xEE (Interaction Term)			0.044	0.558
DM1xSI (Interaction Term)			-0.020	0.826

Table 4. Summary table of the multiple regression analysis for Behavioral Intention, including interaction terms with Gender as a Moderator

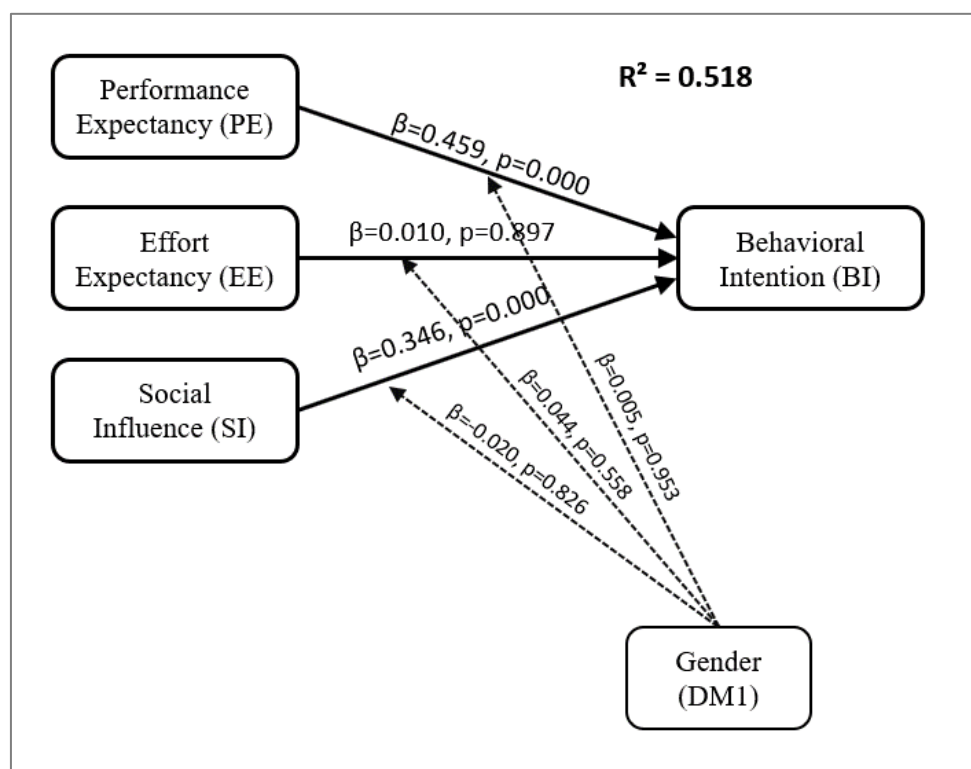


Figure 36. Results of multiple regression analysis for Behavioral Intention, including interaction terms with Gender as a Moderator

Next, we perform a separate hierarchical regression for Age, incorporating interaction terms to explore the impact of age on these relationships: DM2xPE, DM2xEE, DM2xSI. The inclusion of these interaction terms resulted in an increase in R^2 to 0.552, indicating that the model explained 55.2% of the variance in behavioral intention (table 5, 40 & 41). The R^2 change of 0.036 ($p = 0.078$) suggests that adding the interaction terms accounted for an additional 3.6% of the variance in BI. The coefficients in the second model reveal that the interaction term between age and performance expectancy (DM2xPE) was significant ($\beta = 0.237$, $p = 0.020$), indicating that age moderates the relationship between performance expectancy and behavioral intention (table 42). This implies that the effect of performance expectancy on behavioral intention increases with age. This indicates that performance expectancy might be more relevant or influential for older users in terms of shaping their intentions to use technology. The interaction term between age and effort expectancy (DM2xEE) was also significant but in the negative direction ($\beta = -0.150$, $p = 0.048$). This implies that as age increases, the impact of effort expectancy on behavioral intention decreases. The interaction term between age and social influence (DM2xSI) was not significant ($\beta = -0.067$, $p = 0.465$), indicating that age does not significantly moderate the effect of social influence on behavioral intention (figure 37). The above results suggest that older and younger respondents may perceive the ease of use and performance benefits of e-tendering applications differently, influencing their intentions to adopt the technology.

	R²	F	Beta	Sig.
BI (Behavioral Intention, Dependent Variable)	0.552	19.162, p=0.000		
PE (Performance Expectancy, Predictor)			0.434	0.000
EE (Effort Expectancy, Predictor)			0.050	0.506
SI (Social Influence, Predictor)			0.345	0.000
DM2 (Age, Predictor)			0.034	0.608
DM2xPE (Interaction Term)			0.237	0.020
DM2xEE (Interaction Term)			-0.150	0.048
DM2xSI (Interaction Term)			-0.067	0.465

Table 5. Summary table of the multiple regression analysis for Behavioral Intention, including interaction terms with Age as a Moderator

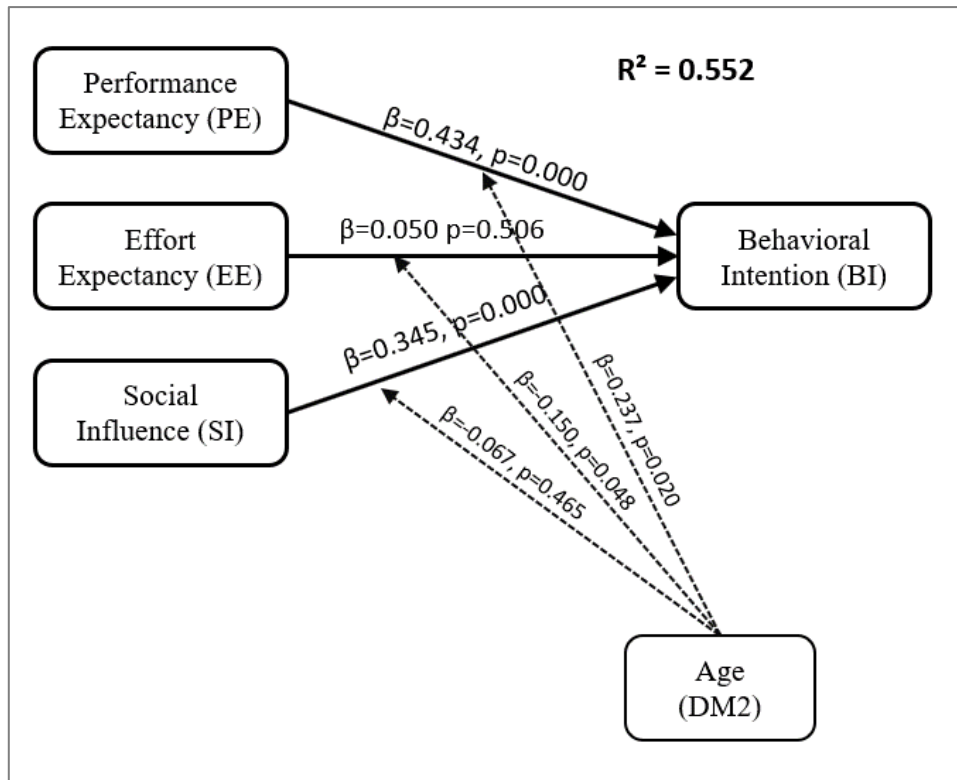


Figure 37. Results of multiple regression analysis for Behavioral Intention, including interaction terms with Age as a Moderator

The above process is repeated for Experience and Voluntariness of Use, with each moderator evaluated in separate hierarchical regressions to independently assess their moderating effects. For Experience we incorporated two interaction terms to explore the impact of experience: EX1xEE and EX1xSI. The R^2 increased to 0.556, suggesting that the inclusion of the interaction terms explained an additional 3.9% of the variance in BI (table 6 & 43). The change in R^2 was statistically significant (F change = 3.248, $p = 0.025$), indicating that the second model was indeed improved (table 44). Examining the coefficients (table 45) in the second model, we found that the moderator EX1 is statistically significant ($\beta = 0.165, p = 0.019$), but the interaction terms are not: EX1xEE ($\beta = -0.112, p = 0.106$), EX1xSI ($\beta = 0.096, p = 0.169$). The significance of the moderator variable alone suggests that it has a direct effect on the dependent variable. This means the moderator impacts the outcome independently of how it affects the relationship between the main predictors and the dependent variable. Sometimes, non-significant interaction effects could be due to insufficient power or small effect sizes that are hard to detect with the available sample size. In any case, the non-significant interaction terms suggest that the effect of the main predictors on the dependent variable does not vary at different levels of the moderator.

This means that experience does not significantly moderate the effects of EE, and SI on BI (figure 38).

	R²	F	Beta	Sig.
BI (Behavioral Intention, Dependent Variable)	0.556	22.912, p=0.000		
PE (Performance Expectancy, Predictor)			0.440	0.000
EE (Effort Expectancy, Predictor)			0.016	0.829
SI (Social Influence, Predictor)			0.338	0.000
EX1 (Experience, Predictor)			0.165	0.019
EX1xEE (Interaction Term)			-0.112	0.106
EX1xSI (Interaction Term)			0.096	0.169

Table 6. Summary table of the multiple regression analysis for Behavioral Intention, including interaction terms with Experience as a Moderator

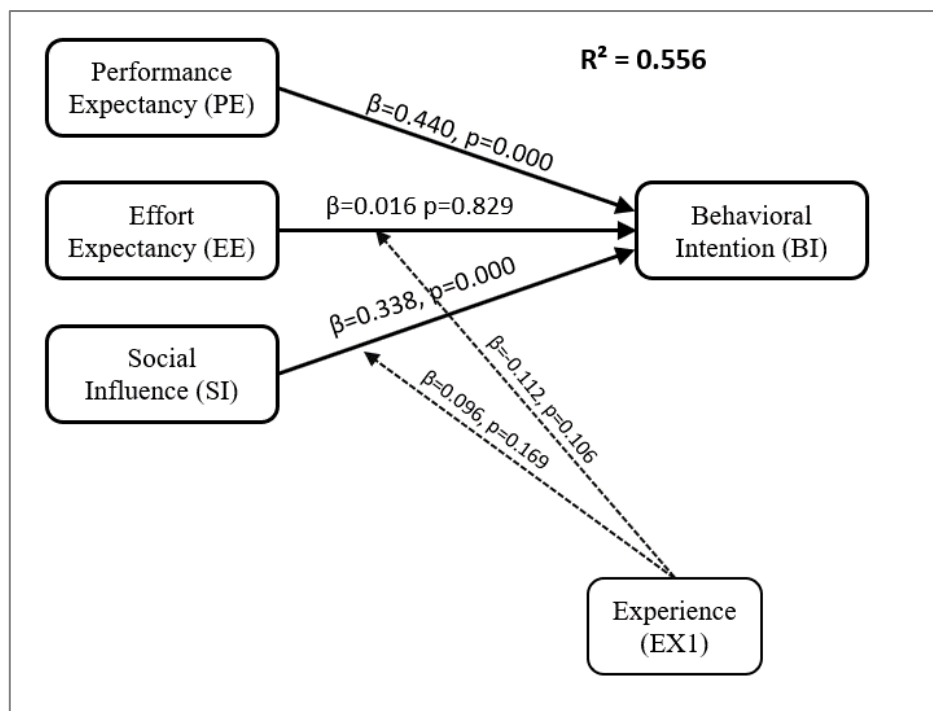


Figure 38. Results of multiple regression analysis for Behavioral Intention, including interaction terms with Experience as a Moderator

For the analysis of Voluntariness of Use (VU) as a moderator, we included the interaction term VU1xSI to explore its impact on Behavioral Intention (BI).

Upon adding the interaction term in the second model, the R^2 increased slightly to 0.530, suggesting that the inclusion of the interaction term explained an additional 1.4% of the variance in BI (table 7 & 46). However, this change in R^2 was not statistically significant (F change = 1.612, $p = 0.204$), indicating that the interaction term did not significantly improve the model (table 47). Examining the coefficients in the second model (table 48), we found that the interaction term VU1xSI was not significant ($\beta = 0.092$, $p = 0.192$). This suggests that Voluntariness of Use does not significantly moderate the effect of Social Influence on Behavioral Intention. Thus, regardless of the level of perceived voluntariness, the influence of colleagues and superiors remains the same as in initial model in shaping individuals' intentions to use e-tendering applications (figure 39).

	R²	F	Beta	Sig.
BI (Behavioral Intention, Dependent Variable)	0.530	25.013, p=0.000		
PE (Performance Expectancy, Predictor)			0.438	0.000
EE (Effort Expectancy, Predictor)			-0.016	0.834
SI (Social Influence, Predictor)			0.358	0.000
VU1 (Voluntariness of Use, Predictor)			0.080	0.229
VU1xSI (Interaction Term)			0.092	0.192

Table 7. Summary table of the multiple regression analysis for Behavioral Intention, including interaction terms with Voluntariness of Use as a Moderator

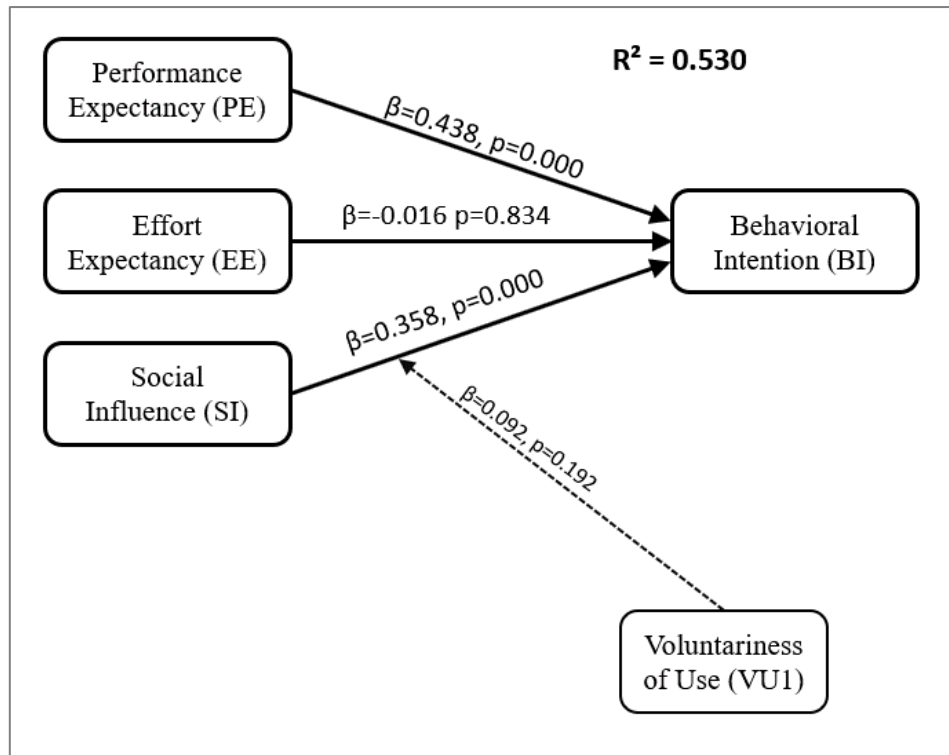


Figure 39. Results of multiple regression analysis for Behavioral Intention, including interaction terms with Voluntariness of Use as a Moderator

4.3.3 Regression Analysis for Use Behavior

In this analysis, regression analysis enables us to evaluate the direct effects of Behavioral Intention (BI) and Facilitating Conditions (FC) on Use Behavior (UB), and to investigate the moderating effects of the demographic variables Age (DM2) and Experience (EX1). The analysis begins with an initial multiple linear regression to understand the direct effects of BI and FC on UB. After the initial analysis we perform a separate hierarchical regression for Age and Experience. To ensure accurate interpretation and to mitigate multicollinearity issues, we standardize all items in the model by transforming them into Z-scores.

The regression analysis for Use Behavior (UB) with Behavioral Intention (BI) and Facilitating Conditions (FC) as predictors reveals significant findings. The model summary shows that the predictors explain 55.7% of the variance in Use Behavior ($R^2 = 0.557$), indicating a substantial portion of the variance in UB can be accounted for by BI and FC (table 8 & 49). The ANOVA table (table 50) supports the significance of the model, with an F value of 71.774 and a p-value of 0.000, suggesting that the model is statistically significant, and the predictors collectively contribute to explaining the variance in UB.

Examining the coefficients, both predictors are statistically significant. Behavioral Intention (BI) has a standardized coefficient (β) of 0.375 and a p-value of 0.000, indicating a strong positive effect on Use Behavior (table 51). This implies that higher behavioral intention significantly predicts increased use behavior of e-tendering applications. Facilitating Conditions (FC) also show a significant positive effect on Use Behavior, with a standardized coefficient (β) of 0.471 and a p-value of 0.000. This indicates that better facilitating conditions, such as availability of resources and support, lead to higher use behavior of the technology. Overall, the results demonstrate that both Behavioral Intention and Facilitating Conditions are critical determinants of Use Behavior in the context of e-tendering applications (figure 40). The significant positive relationships highlight the importance of fostering a supportive environment and ensuring strong user intentions to enhance the actual use of technology.

	R²	F	Beta	Sig.
UB (Use Behavior, Dependent Variable)	0.557	71.774, p=0.000		
BI (Behavioral Intention, Predictor)			0.375	0.000
FC (Facilitating Conditions, Predictor)			0.471	0.000

Table 8. Summary table of the multiple regression analysis for Use Behavior

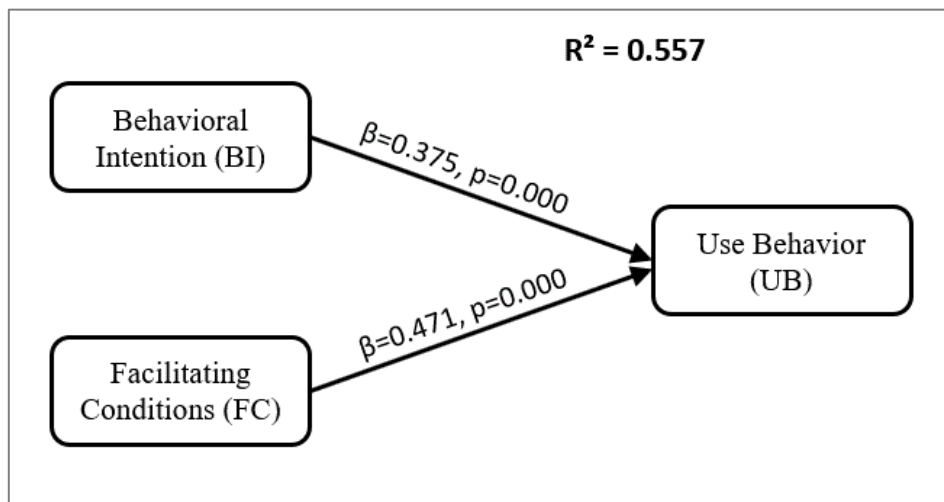


Figure 40. Results of multiple regression analysis in which Use Behavior was regressed on Behavioral Intention (BI) and Facilitating Conditions (FC).

Having determined the direct effects, we proceed to hierarchical regression analyses to assess the moderating effects of the demographic variables (Age, Experience).

To examine the moderating effect of age we introduce one interaction term into the model: DM2xFC. When the interaction term DM2xFC is added, the R^2 increases to 0.565, but with no significant increase in explained variance (F change = 0.986, p = 0.376), indicating that the interaction term did not significantly improve the model (table 9, 52 & 53). In the coefficients table (table 54), both BI (β = 0.375, p = 0.000) and FC (β = 0.453, p = 0.000) remain significant predictors of UB, suggesting that higher behavioral intention and better facilitating conditions significantly predict increased use behavior. However, the interaction term DM2xFC (β = -0.013, p = 0.831) is not significant, indicating that age does not significantly moderate the effect of facilitating conditions on use behavior (figure 41). This suggests that the impact of facilitating conditions on use behavior is consistent across different age groups.

	R²	F	Beta	Sig.
UB (Use Behavior, Dependent Variable)	0.565	36.371, p=0.000		
BI (Behavioral Intention, Predictor)			0.375	0.000
FC (Facilitating Conditions, Predictor)			0.453	0.000
DM2 (Age, Predictor)			0.089	0.165
DM2xFC (Interaction Term)			-0.013	0.831

Table 9. Summary table of the multiple regression analysis for Use Behavior, including interaction term with Age as a Moderator

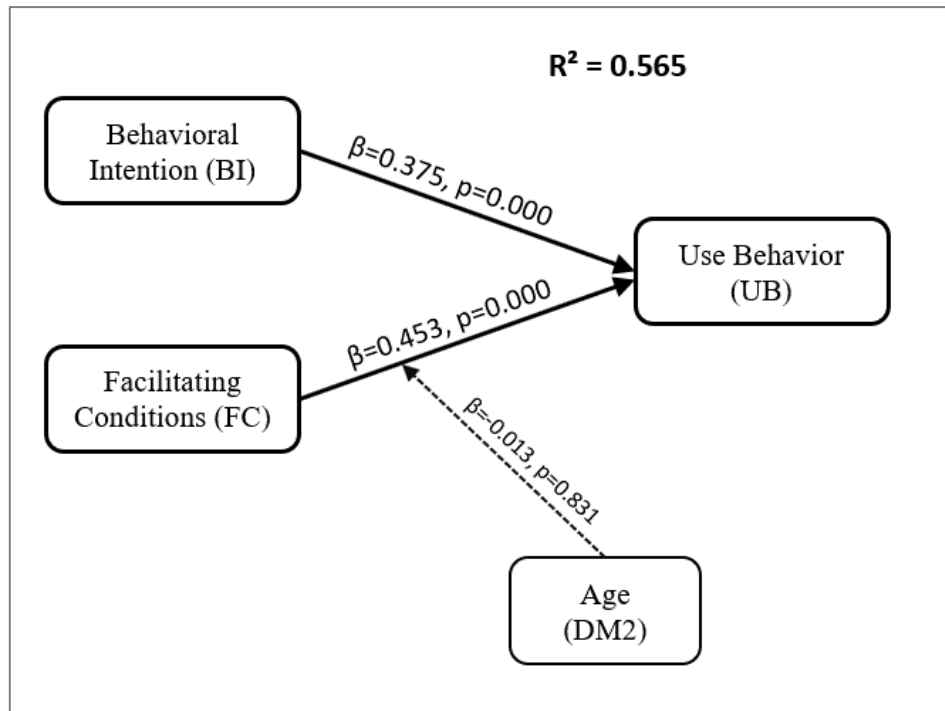


Figure 41. Results of multiple regression analysis for Use Behavior, including interaction term with Age as a Moderator

To examine the moderating effect of Experience we introduce one interaction term into the model: EX1xFC. When the moderator and the interaction term EX1xFC is added in the second model (table 10, 55 & 56), the R^2 increases to 0.643, suggesting a significant increase in explained variance (F change = 13.353, $p = 0.000$). The significance of EX1 alone suggests that it has a direct, positive effect on User Behavior independent of its interaction with Facilitating Conditions. Experience enhances User Behavior, which might indicate that more experienced users are more likely to engage in the desired behavior regardless of the facilitating conditions. However, the interaction term EX1xFC ($\beta = -0.015$, $p = 0.804$) is not significant (table 57), which implies that while Experience itself is important, its effect on how Facilitating Conditions influence User Behavior isn't statistically evident. This might suggest that the enabling environment (Facilitating Conditions) affects User Behavior similarly across different levels of user experience. In summary, while the Experience is an important direct predictor of User Behavior, its moderating effect on the relationship between Facilitating Conditions and User Behavior isn't supported by this analysis (figure 42).

	R²	F	Beta	Sig.
UB (Use Behavior, Dependent Variable)	0.643	50.341, p=0.000		
BI (Behavioral Intention, Predictor)			0.370	0.000
FC (Facilitating Conditions, Predictor)			0.271	0.001
EX1 (Experience, Predictor)			0.352	0.000
EX1xFC (Interaction Term)			-0.015	0.804

Table 10. Summary table of the multiple regression analysis for Use Behavior, including interaction term with Experience as a Moderator

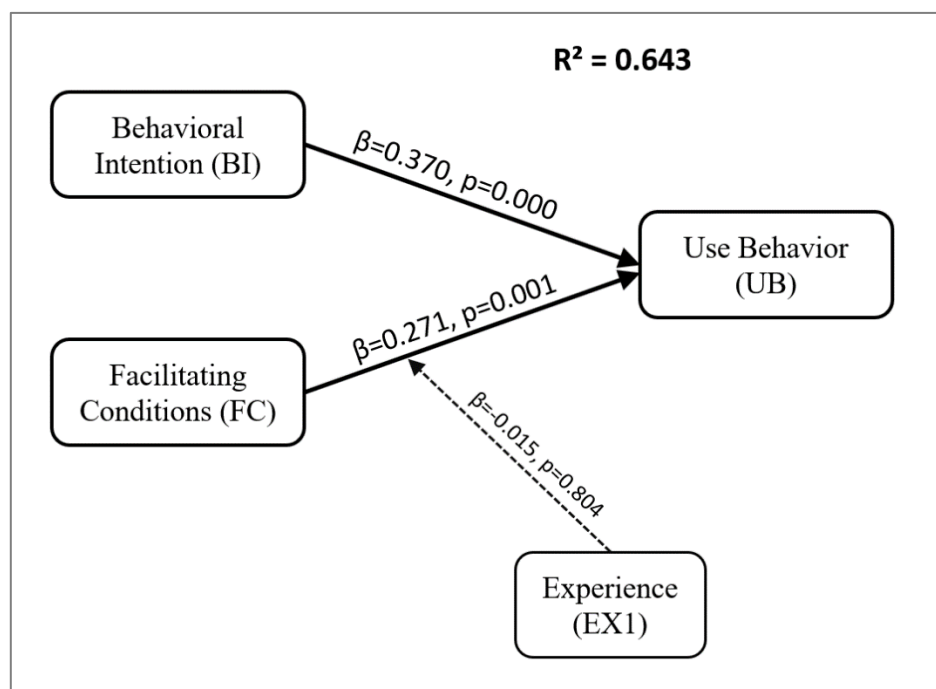


Figure 42. Results of multiple regression analysis for Use Behavior, including interaction term with Experience as a Moderator

4.4 Summary and hypotheses testing

The analysis of the UTAUT model revealed several key findings regarding the adoption of e-tendering applications.

Performance Expectancy (PE) and Social Influence (SI) significantly positively affect Behavioral Intention (BI) to use e-tendering applications, with regression coefficients of $\beta = 0.449$ ($p < 0.001$) for PE and $\beta = 0.343$ ($p < 0.001$) for SI. This highlights that perceived usefulness and social pressures are crucial drivers of behavioral intention. Effort Expectancy (EE) did not have a significant effect on BI, with a regression coefficient of $\beta = 0.018$ ($p = 0.803$). This indicates that the perceived ease of use does not play a critical role in the decision to adopt e-tendering applications within this context.

Behavioral Intention (BI) and Facilitating Conditions (FC) significantly positively influence Use Behavior (UB), with regression coefficients of $\beta = 0.375$ ($p < 0.001$) for BI and $\beta = 0.471$ ($p < 0.001$) for FC. This indicates that both the intention to use and the availability of necessary resources and support are critical in determining actual usage behavior.

In terms of moderating effects, the results showed that Gender does not significantly moderate the effects of PE (DM1xPE: $\beta = 0.005$, $p = 0.953$), EE (DM1xEE: $\beta = 0.044$, $p = 0.558$), and SI (DM1xSI: $\beta = -0.020$, $p = 0.826$) on BI, indicating that the relationships between these constructs and behavioral intention are consistent across genders. Age was found to significantly moderates the effects of PE (DM2xPE: $\beta = 0.237$, $p = 0.020$) and EE (DM2xEE: $\beta = -0.150$, $p = 0.048$) on BI, but not SI (DM2xSI: $\beta = -0.067$, $p = 0.465$). This suggests that older and younger individuals experience different impacts of performance expectancy and effort expectancy on their behavioral intentions. Experience with similar technologies does not significantly moderate the effects of EE (EX1xEE: $\beta = -0.112$, $p = 0.106$) and SI (EX1xSI: $\beta = 0.096$, $p = 0.169$) on BI, indicating that prior experience does not alter the influence of effort expectancy and social influence on behavioral intention. Similarly, Voluntariness of Use does not significantly moderate the effect of SI on BI (VU1xSI: $\beta = 0.092$, $p = 0.192$), suggesting that the perceived voluntariness does not change the impact of social influence on behavioral intention. For the relationship between FC and UB, neither Age (DM2xFC: $\beta = -0.013$, $p = 0.831$) nor Experience (EX1xFC: $\beta = -0.015$, $p = 0.804$) significantly moderates this effect. This indicates that facilitating conditions consistently influence use behavior, regardless of the user's age or prior experience with similar technologies.

Thus, the summary of the hypotheses testing is presented below (figure 43, table 11):

Hypotheses Related to Direct Effects of UTAUT Constructs

- **Hypothesis 1 (H1):** Performance expectancy positively affects the behavioral intention to use e-tendering applications. → **Supported**
- **Hypothesis 2 (H2):** Effort expectancy positively affects the behavioral intention to use e-tendering applications. → **Not Supported**
- **Hypothesis 3 (H3):** Social influence positively affects the behavioral intention to use e-tendering applications. → **Supported**
- **Hypothesis 4 (H4):** Behavioral intention positively affects the actual use of e-tendering applications. → **Supported**
- **Hypothesis 5 (H5):** Facilitating conditions positively affect the actual use of e-tendering applications. → **Supported**

Hypotheses Related to Moderating Effects

Moderating Effects of Gender

- **Hypothesis 6 (H6):** Gender significantly moderates the effects of performance expectancy, effort expectancy, and social influence on the behavioral intention. → **Not Supported**

Moderating Effects of Age

- **Hypothesis 7 (H7):** Age significantly moderates the effects of performance expectancy, effort expectancy, and social influence on the behavioral intention. → **Partially Supported**
- **Hypothesis 8 (H8):** Age significantly moderates the effects of facilitating conditions on the actual use of e-tendering applications. → **Not Supported**

Moderating Effects of Experience

- **Hypothesis 9 (H9):** Experience significantly moderates the effects of effort expectancy and social influence on the behavioral intention. → **Not Supported**
- **Hypothesis 10 (H10):** Experience significantly moderates the effects of facilitating conditions on the actual use of e-tendering applications. → **Not Supported**

Moderating Effects of Voluntariness of Use

- **Hypothesis 11 (H11):** Voluntariness of use significantly moderates the effects of social influence on the behavioral intention. → **Not Supported**

Null Hypothesis	Beta Coefficient	Significant (p<0.05)	Result
Hypothesis 1 (H1)	0.449	P<0.001	Supported
Hypothesis 2 (H2)	0.018	P=0.803	Not Supported
Hypothesis 3 (H3)	0.343	P<0.001	Supported
Hypothesis 4 (H4)	0.375	P<0.001	Supported
Hypothesis 5 (H5)	0.471	P<0.001	Supported
Hypothesis 6 (H6)	DM1xPE: 0.005 DM1xEE: 0.044 DM1xSI: -0.020	DM1xPE: P=0.953 DM1xEE: P=0.558 DM1xSI: P=0.826	Not Supported
Hypothesis 7 (H7)	DM2xPE: 0.237 DM2xEE: -0.150 DM2xSI: -0.067	DM2xPE: P=0.020 DM2xEE: P=0.048 DM2xSI: P=0.465	Partially Supported
Hypothesis 8 (H8)	DM2xFC: -0.013	DM2xFC: P=0.831	Not Supported
Hypothesis 9 (H9)	EX1xEE: -0.112 EX1xSI: 0.096	EX1xEE: P=0.106 EX1xSI: P=0.169	Not Supported
Hypothesis 10 (H10)	EX1xFC: -0.015	EX1xFC: P=0.804	Not Supported
Hypothesis 11 (H11)	VU1xSI: 0.092	VU1xSI: P=0.192	Not Supported

Table 11. Hypothesis testing

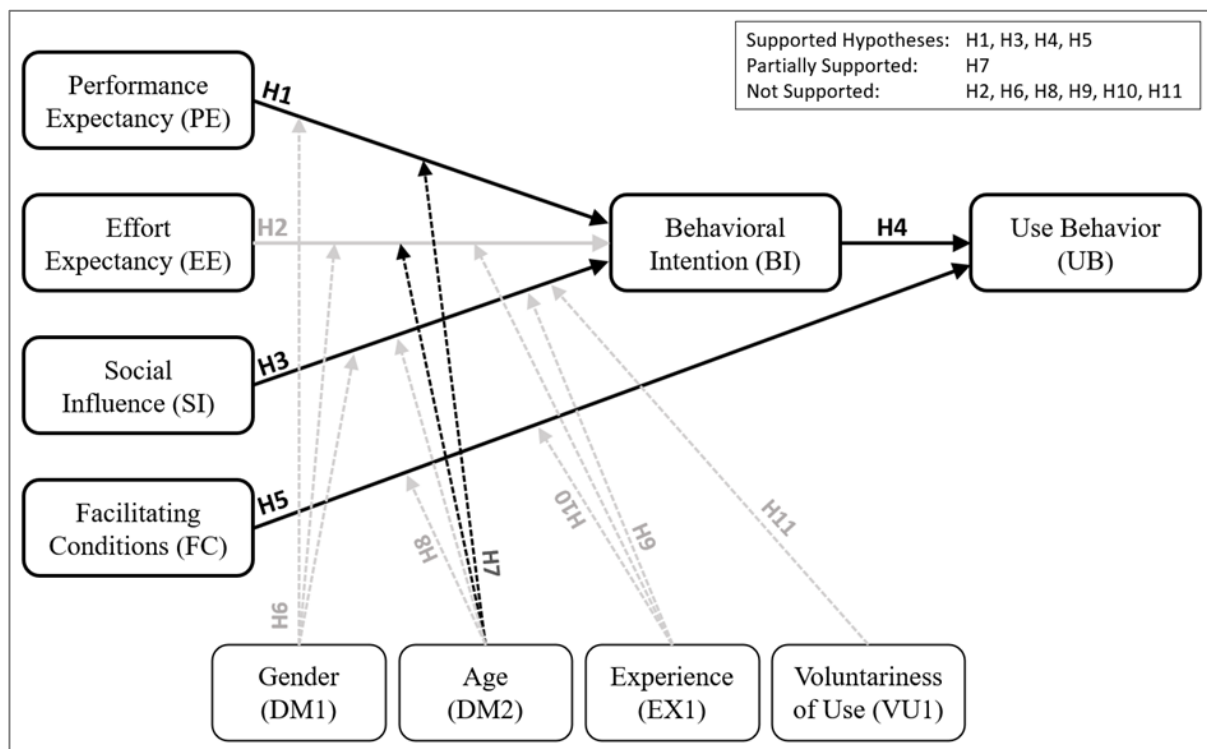


Figure 43. Results of Hypothesis testing

Chapter 5: Discussion and Conclusions

5.1 Discussion & Conclusions

This dissertation explored the factors influencing the adoption of electronic (e-tendering) applications by Greek companies using the Unified Theory of Acceptance and Use of Technology (UTAUT) as the theoretical framework. The key constructs of the UTAUT model — Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) — were examined in relation to Behavioral Intention (BI) and Use Behavior (UB). The results underscore the complexity of technology adoption in organizational settings, revealing several critical insights.

Performance Expectancy (PE) and Social Influence (SI) emerged as significant predictors of Behavioral Intention (BI). This finding aligns with previous studies indicating that the perceived usefulness of technology (Davis, 1989) and social factors (Venkatesh & Davis, 2000) play crucial roles in technology adoption decisions. Users are more likely to adopt e-tendering applications if they believe these tools will enhance their job performance and if influential colleagues endorse their use.

The significant positive effect of Performance Expectancy on Behavioral Intention aligns with the core premise of the UTAUT model, highlighting the critical role of perceived performance benefits in driving technology adoption. In the context of Greek companies, where operational efficiency and cost-effectiveness are paramount, the perceived utility of e-tendering applications in enhancing job performance is particularly influential. This finding is supported by Venkatesh et al. (2003), who found that Performance Expectancy was a key determinant of Behavioral Intention across various contexts.

The significant positive effect of Social Influence indicates that the opinions and behaviors of colleagues, industry peers, superiors, and other influential individuals within the organization strongly influence individuals' intentions to use e-tendering applications. This finding is consistent with prior studies and emphasizes the importance of social factors in technology adoption (Ajzen, 1991). In Greek companies, where hierarchical structures and collective decision-making are common, the support and endorsement of e-tendering applications by key influencers can significantly drive adoption. This underscores the need for organizational strategies that leverage social endorsements and foster a supportive environment for technology adoption. This is in line with findings by Wu et al. (2011), who highlighted the importance of social influence in technology acceptance.

Effort Expectancy (EE), however, did not significantly influence Behavioral Intention (BI). This suggests that, in the context of e-tendering applications, ease of use is not a primary concern for Greek companies. This finding diverges from some earlier studies that emphasized the importance of ease of use in technology adoption (Venkatesh & Bala, 2008), highlighting the contextual differences in technology adoption. It is possible that in professional settings where e-tendering applications are used, users are more focused on the effectiveness and benefits of the technology rather than its ease of use. That means that users are willing to overlook usability issues if the perceived benefits of the technology are substantial (Venkatesh & Davis, 2000). Furthermore, the finding could be attributed to the increasing familiarity and comfort with digital tools among professionals, or to the professional training and support typically available in organizational contexts, which reduces the perceived effort required to use new technologies.

Both Behavioral Intention (BI) and Facilitating Conditions (FC) were found to significantly predict actual Use Behavior (UB). This supports the notion that the intention to use technology, coupled with the availability of necessary resources and support, are crucial determinants of actual usage behavior. The significant positive effect of Facilitating Conditions indicates that the availability of resources, training, and technical support are critical for the successful adoption and use of e-tendering applications (Venkatesh et al., 2003). This finding is consistent with previous research highlighting the importance of organizational support in technology adoption (Teo et al., 2008; DeLone & McLean, 1992). In the Greek context, where financial and technical resources may be limited, ensuring adequate support and infrastructure is particularly crucial. Organizations that provide robust infrastructure and support mechanisms are more likely to see higher adoption rates of e-tendering applications.

The study also explored the moderating effects of demographic variables such as Age, Gender, Experience, and Voluntariness of Use on the relationships between UTAUT constructs and technology adoption behaviors. The analysis revealed that Age partially moderates the relationships between Performance Expectancy (PE) and Effort Expectancy (EE) on Behavioral Intention (BI). Older users placed greater emphasis on performance benefits, while the ease of use was less critical for them, compared to younger users. This aligns with research suggesting that older adults prioritize the utility of technology over its usability (Morris & Venkatesh, 2000).

Gender, Experience, and Voluntariness of Use did not significantly moderate any of the examined relationships. This suggests that while certain demographic factors may influence technology adoption, their impact may not be as pronounced as the core constructs of the UTAUT model (Venkatesh et al., 2003). The lack of significant moderation by gender indicates that the relationships between Performance Expectancy, Effort Expectancy, Social Influence, and Behavioral Intention are consistent across male and female users. Similarly, the non-significant moderation by experience suggests that prior experience with similar technologies does not alter the influence of these factors on Behavioral Intention. The findings regarding Voluntariness of Use indicate that the perceived voluntariness of using e-tendering applications does not significantly change the impact of social influence on Behavioral Intention.

5.2 Implications

The implications of this study are both theoretical and practical. Theoretically, the study reinforces the validity of the UTAUT model in the context of e-tendering applications and underscores the importance of Performance Expectancy and Social Influence as key determinants of technology adoption.

Practically, the findings offer several actionable insights for organizations aiming to adopt e-tendering applications. Emphasizing the performance benefits of these technologies is crucial. Companies should focus on demonstrating how e-tendering can enhance operational efficiency, reduce costs, and improve transparency in procurement processes. Highlighting these benefits can significantly drive Behavioral Intention to adopt e-tendering systems (Venkatesh et al., 2003). Leveraging Social Influence is another key strategy. Organizations can benefit from involving respected figures within the company to advocate for the new technology. This approach can create a supportive environment that encourages adoption. Peer influence, particularly from colleagues who are early adopters, can also be harnessed through structured change management programs and internal marketing campaigns. By showcasing successful use cases and involving influential employees as champions, companies can enhance the overall acceptance and integration of e-tendering applications (Ajzen, 1991). Providing comprehensive support and resources is crucial in facilitating the actual use of e-tendering applications. This includes investing in robust IT infrastructure, offering extensive training programs, and ensuring that technical support is readily

available. Such measures will address the Facilitating Conditions necessary for successful technology adoption. Ensuring that employees have access to the necessary tools, resources, and support systems can mitigate potential barriers to effective usage (DeLone & McLean, 1992).

For policymakers and managers, these insights are invaluable in guiding the design and implementation of strategies to promote e-tendering applications. Policymakers can develop frameworks that emphasize the efficiency and effectiveness of e-tendering systems, potentially incorporating incentives for companies that adopt these technologies. Managers should focus on creating an environment that supports technology adoption through clear communication of benefits, strong leadership endorsement, and adequate resource allocation. Moreover, addressing potential concerns related to data security and privacy can further facilitate adoption. Ensuring that e-tendering systems comply with regulatory standards and that robust cybersecurity measures are in place can alleviate fears related to data breaches and enhance trust in the new technology (Bélanger & Carter, 2008). This aspect is particularly critical in a digital age where data security concerns can significantly impede technology adoption.

In conclusion, the practical implications of this study provide a clear roadmap for organizations and policymakers aiming to drive the adoption of e-tendering applications. By focusing on performance benefits, leveraging social influence, providing comprehensive support, and addressing security concerns, they can enhance adoption rates and, ultimately, improve organizational efficiency and competitiveness. These strategies offer a structured approach to managing the complexities of technology adoption in a corporate setting.

5.3 Study limitations

The findings of this study contribute to the understanding of e-tendering adoption in Greek companies by highlighting the importance of perceived benefits, social influence, and facilitating conditions. The study enriches the technology adoption literature by providing empirical evidence from a specific cultural and economic context. Practically, the results offer actionable insights for businesses and policymakers to design effective strategies for promoting e-tendering adoption. By addressing the identified drivers and barriers, Greek companies can enhance their procurement processes, achieving greater efficiency, transparency, and competitiveness in the market.

Despite its contributions, this study has several limitations. First, the study relied on a quantitative research methodology using structured questionnaires. While this approach allows for the collection of data from a broad sample, it also comes with inherent limitations. Self-reported data can be subject to biases such as social desirability bias. Additionally, the accuracy of the responses can be affected by the respondents' interpretation of the questions and their willingness to participate fully. This could potentially skew the data, making it less reliable (Podsakoff et al., 2003). Second, the sampling method used was non-probability sampling, which, while practical and cost-effective, may limit the representativeness of the sample. The findings are based on responses from a specific subset of Greek companies that were willing to participate in the study. This method may not capture the full diversity of opinions and experiences across the entire population of Greek businesses using or considering e-tendering applications. As a result, the findings may not be fully generalizable to all Greek companies or to companies in other countries with different cultural and economic contexts (Etikan, Musa, & Alkassim, 2016). Third, the study's sample size, although adequate for statistical analysis, still poses limitations regarding the robustness of the findings. A larger sample size could provide more reliable and generalizable results, reducing the margin of error and increasing the confidence in the observed relationships. Future studies could benefit from expanding the sample size to include a broader range of companies, both in terms of size and industry sector (Cohen, 1988). Fourth, the research focused exclusively on Greek companies, which limits the ability to generalize the findings to other cultural or economic contexts. Greece has unique socio-economic characteristics and business practices that may influence the adoption of e-tendering applications. Therefore, the findings of this study may not be directly applicable to companies operating in different countries or regions with varying levels of technological infrastructure, regulatory environments, and cultural attitudes towards technology adoption (Vassilakis et al., 2016). Fifth, the study primarily investigated the key constructs of the UTAUT model without delving deeply into other potential factors that might influence technology adoption. Factors such as organizational culture and specific industry regulations were not explicitly examined. Including these additional variables in future research could provide a more comprehensive understanding of the factors influencing e-tendering adoption. Finally, the cross-sectional nature of the study captures a snapshot of the current state of e-tendering adoption but does not account for changes over time. Technology adoption is a dynamic process that can evolve with changes in technology, organizational priorities, and external factors. Longitudinal studies that track changes in adoption behavior over time would

provide deeper insights into how e-tendering applications are integrated into organizational practices and how the factors influencing adoption may shift.

In summary, while this study offers significant contributions to understanding the adoption of e-tendering applications among Greek companies, these limitations highlight areas for further research. Addressing these limitations in future studies could enhance the robustness and generalizability of the findings, providing a more comprehensive picture of technology adoption in various contexts. Future research should consider larger and more diverse samples to enhance representativeness, longitudinal designs that could provide deeper insights into the long-term adoption behaviors, and the inclusion of additional influencing factors to build a more holistic understanding of e-tendering adoption.

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Appendix A: Tables

#	Code	Question text
1	DM1	Gender
2	DM2	Age
3	DM3	Education Level
4	DM4	Position within the Company
5	DM5	Business Unit within the Company that your primary responsibilities lie
6	DM6	Sector in which the Company operates
7	DM7	Size of the Company
8	DM8	Your role in the decision-making process for digital procurement solutions (e.g. e-tendering applications) at the Company

Table 12. Demographics (DM) Questions

#	Code	Question text
9	EX1	Your experience with e-tendering applications

Table 13. Experience (EX) Questions

#	Code	Question text
<i>in a 5-point scale (1=strongly disagree, 5=strongly agree):</i>		
10	VU1	I have the freedom to choose whether or not to use e-tendering applications at my work.

Table 14. Voluntariness of Use (VU) Questions

#	Code	Question text
<i>in a 5-point scale (1=strongly disagree, 5=strongly agree):</i>		
11	UB1	I use e-tendering applications regularly in my procurement activities.
12	UB2	E-tendering applications are fully integrated into my daily work.
13	UB3	I utilize all the available features of e-tendering applications.

Table 15. Use Behavior (UB) Questions

#	Code	Question text
<i>in a 5-point scale (1=strongly disagree, 5=strongly agree):</i>		
14	BI1	I intend to use e-tendering applications in my future procurement activities.
15	BI2	I will recommend e-tendering applications to peers in the procurement field.
16	BI3	Assuming I have access to an e-tendering application, I predict that I would use it frequently.

Table 16. Behavioral Intention (BI) Questions

#	Code	Question text
<i>in a 5-point scale (1=strongly disagree, 5=strongly agree):</i>		
17	PE1	Using e-tendering applications would improve the efficiency of our procurement processes.
18	PE2	I believe that using e-tendering applications would help minimize errors in our procurement processes.
19	PE3	Using e-tendering applications would improve the transparency of our procurement processes.

Table 17. Performancy Expectancy (PE) Questions

#	Code	Question text
<i>in a 5-point scale (1=strongly disagree, 5=strongly agree):</i>		
20	EE1	I find e-tendering applications easy to use.
21	EE2	Learning to operate an e-tendering application would be easy for me.
22	EE3	E-tendering applications require minimal effort to maintain and update.

Table 18. Effort Expectancy (EE) Questions

#	Code	Question text
<i>in a 5-point scale (1=strongly disagree, 5=strongly agree):</i>		
23	SI1	People whose opinions I value think that I should use e-tendering applications in my work.
24	SI2	Companies that we regularly do business with use e-tendering applications in their procurement processes.
25	SI3	My direct supervisor encourages me to use e-tendering applications in my work.

Table 19. Social Influence (SI) Questions

#	Code	Question text
<i>in a 5-point scale (1=strongly disagree, 5=strongly agree):</i>		
26	FC1	My company provides all necessary resources and technical support to facilitate the effective use of e-tendering applications.
27	FC2	I am well-trained and knowledgeable in using e-tendering applications effectively.
28	FC3	The company allocates adequate financial resources to ensure the effective implementation and ongoing maintenance of e-tendering applications.

Table 20. Facilitating Conditions (FC) Questions

						Mean and Std. Deviation of Composite Items													
						Use Behavior (UB)		Behavioral Intention (BI)		Performance Expectancy (PE)		Effort Expectancy (EE)		Social Influence (SI)		Facilitating Conditions (FC)			
Question Code	Question	Value	Value Label	Frequency	Percent	Mean	Std. Deviation	Mean	Std. Deviation	Mean	Std. Deviation	Mean	Std. Deviation	Mean	Std. Deviation	Mean	Std. Deviation		
DM1	Gender	1	Male	65	55.6%	3.01	1.327	3.67	1.030	3.81	0.901	3.51	0.717	3.15	0.898	3.56	0.949		
		2	Female	52	44.4%	3.12	1.474	3.87	0.945	4.04	0.855	3.61	0.775	3.44	1.137	3.46	1.128		
DM1 Total						117	100.0%	3.06	1.389	3.76	0.994	3.91	0.885	3.56	0.741	3.28	1.017	3.52	1.029
DM2	Age	1	24 years old or younger	1	0.9%	4.67	-	3.67	-	5.00	-	4.33	-	4.33	-	3.67	-		
		2	25 to 34 years old	20	17.1%	2.30	1.279	3.50	0.902	3.77	0.795	3.48	0.729	3.13	1.023	3.28	1.033		
		3	35 to 44 years old	39	33.3%	2.94	1.374	3.68	0.981	3.75	0.975	3.65	0.666	3.16	0.991	3.24	1.095		
		4	45 to 54 years old	36	30.8%	3.35	1.391	4.04	0.850	4.06	0.725	3.60	0.755	3.42	1.006	3.79	0.859		
		5	55 to 64 years old	17	14.5%	3.41	1.228	3.57	1.348	4.04	1.073	3.31	0.924	3.37	1.148	3.78	1.020		
		6	65 years old or older	4	3.4%	3.42	1.708	4.25	0.877	3.92	0.833	3.42	0.569	3.25	1.067	3.75	1.450		
DM2 Total						117	100.0%	3.06	1.389	3.76	0.994	3.91	0.885	3.56	0.741	3.28	1.017	3.52	1.029
DM3	Education Level	1	Primary - Lower Secondary Education Diploma	0	0.0%	-	-	-	-	-	-	-	-	-	-	-	-	-	
		2	Upper Secondary Education Diploma	10	8.5%	3.57	1.595	4.10	1.287	4.03	1.191	3.77	0.847	3.80	1.307	3.90	1.449		
		3	Post Secondary Education Diploma	7	6.0%	2.86	1.372	3.57	0.787	4.10	0.659	3.52	0.539	3.00	0.577	3.95	0.989		
		4	Higher Education Degree	41	35.0%	3.02	1.440	3.74	1.021	3.89	0.979	3.52	0.830	3.24	1.041	3.36	1.015		
		5	Master's Degree	58	49.6%	2.99	1.330	3.72	0.949	3.87	0.795	3.55	0.694	3.22	0.972	3.49	0.951		
		6	Doctoral Degree	1	0.9%	4.67	-	5.00	-	4.67	-	3.67	-	4.67	-	4.67	-		
DM3 Total						117	100.0%	3.06	1.389	3.76	0.994	3.91	0.885	3.56	0.741	3.28	1.017	3.52	1.029
DM4	Position within the Company	1	Junior Staff	4	3.4%	2.92	2.217	3.58	0.569	3.33	1.563	3.25	0.833	3.00	1.743	2.92	1.450		
		2	Experienced Staff	39	33.3%	3.15	1.331	3.78	0.938	3.91	0.808	3.62	0.711	3.50	0.809	3.44	0.986		
		3	Middle Management (Head of Department, etc.)	34	29.1%	2.95	1.493	3.97	0.979	4.16	0.697	3.68	0.643	3.33	1.070	3.71	1.060		
		4	Senior Management (C-level, Director)	27	23.1%	3.30	1.272	3.83	0.889	3.90	0.951	3.52	0.854	3.25	0.985	3.42	0.963		
		5	Owner	13	11.1%	2.62	1.332	3.08	1.299	3.44	1.031	3.23	0.786	2.62	1.113	3.64	1.118		
DM4 Total						117	100.0%	3.06	1.389	3.76	0.994	3.91	0.885	3.56	0.741	3.28	1.017	3.52	1.029
DM5	Business Unit within the Company that your primary responsibilities lie	1	Procurement/ Supply Chain	51	43.6%	3.04	1.504	3.83	0.958	3.91	0.996	3.76	0.696	3.29	1.075	3.37	1.107		
		2	Information Technology (IT)	7	6.0%	2.81	1.260	3.19	1.317	3.62	0.803	3.24	0.418	2.71	1.268	4.29	0.705		
		3	Administration	34	29.1%	3.24	1.199	3.84	0.999	3.97	0.915	3.45	0.887	3.27	0.986	3.51	0.975		
		4	Human Resources	3	2.6%	4.00	1.000	4.00	0.509	3.78	0.385	3.56	0.509	3.78	0.839	3.56	1.018		
		5	Commercial/ Sales	7	6.0%	2.81	1.783	3.95	0.932	4.14	0.900	3.67	0.793	3.24	1.084	3.76	1.197		
		6	Financial/ Accounting	7	6.0%	2.29	1.079	3.10	1.228	3.62	0.591	3.24	0.317	3.19	0.504	3.14	0.690		
		7	Other	8	6.8%	3.17	1.553	3.79	0.641	4.00	0.309	3.17	0.591	3.67	0.943	3.88	0.925		
DM5 Total						117	100.0%	3.06	1.389	3.76	0.994	3.91	0.885	3.56	0.741	3.28	1.017	3.52	1.029
DM6	Sector in which the Company operates	1	Industry/ Manufacturing	25	21.4%	2.63	1.422	3.63	0.973	3.72	1.061	3.69	0.833	3.00	1.050	3.20	1.041		
		2	Construction	12	10.3%	3.50	1.389	3.83	1.150	3.81	0.989	3.22	0.687	3.53	1.077	3.56	1.473		
		3	Hospitality/ Food Service	4	3.4%	2.50	1.232	3.75	0.569	3.67	1.054	3.67	0.272	3.25	0.419	3.25	0.739		
		4	Retail Trade	6	5.1%	2.89	1.544	3.39	0.574	3.33	1.282	3.44	0.584	3.00	1.011	2.89	0.455		
		5	Transport/ Logistics	6	5.1%	2.56	1.425	4.11	1.089	3.89	1.047	3.72	0.612	3.56	0.807	2.83	1.090		
		6	Telecommunications	5	4.3%	3.67	0.882	3.40	1.011	4.13	1.095	3.40	0.641	3.33	0.972	4.20	0.558		
		7	Energy	12	10.3%	3.33	1.400	4.03	0.822	4.31	0.594	3.69	0.731	3.61	0.908	3.64	0.881		
		8	Financial	1	0.9%	1.00	-	1.00	-	3.00	-	2.67	-	3.00	-	2.67	-		
		9	Health/ Medical	9	7.7%	4.04	1.306	3.89	1.258	3.96	0.716	3.85	0.818	4.00	0.833	4.07	0.846		
		10	IT Services	5	4.3%	3.13	1.386	3.33	1.700	3.73	0.723	3.40	0.723	3.07	1.402	4.13	0.380		
		11	Imports / Trade	7	6.0%	2.86	1.844	4.05	0.651	4.19	0.604	3.24	0.897	2.81	1.303	3.29	1.339		
		12	Other Services	25	21.4%	3.04	1.211	3.88	0.849	4.07	0.687	3.56	0.750	3.20	0.995	3.75	0.909		
DM6 Total						117	100.0%	3.06	1.389	3.76	0.994	3.91	0.885	3.56	0.741	3.28	1.017	3.52	1.029
DM7	Size of the Company	1	Under 50 employees	54	46.2%	2.85	1.402	3.55	1.090	3.70	0.986	3.33	0.777	3.04	1.122	3.28	1.073		
		2	51 to 250 employees	24	20.5%	3.40	1.380	4.01	0.777	4.21	0.604	3.79	0.701	3.68	0.783	3.88	0.967		
		3	Over 250 employees	39	33.3%	3.13	1.363	3.90	0.934	3.90	0.829	3.72	0.638	3.36	0.919	3.62	0.940		
DM7 Total						117	100.0%	3.06	1.389	3.76	0.994	3.91	0.885	3.56	0.741	3.28	1.017	3.52	1.029
DM8	Your role in the decision-making process for digital procurement solutions (e.g. e-tendering applications)	1	Not involved	26	22.2%	2.56	1.460	3.60	0.838	3.88	0.838	3.44	0.810	3.08	1.140	3.00	0.993		
		2	Decision Contributor	61	52.1%	3.24	1.385	3.91	0.974	4.04	0.808	3.64	0.695	3.50	0.904	3.67	1.009		
		3	Lead Decision-Maker	30	25.6%	3.11	1.273	3.60	1.136	3.67	1.039	3.49	0.777	3.01	1.056	3.66	0.984		
DM8 Total						117	100.0%	3.06	1.389	3.76	0.994	3.91	0.885	3.56	0.741	3.28	1.017	3.52	1.029
EX1	Your experience with e-tendering applications	1	No experience	25	21.4%	1.47	0.816	3.21	1.013	3.63	1.033	3.53	0.561	2.55	1.022	2.65	0.920		
		2	Less than 1 year	11	9.4%	2.52	1.187	3.45	0.637	3.67	0.537	3.15	0.780	3.36	0.547	2.79	0.749		
		3	1 to 3 years	22	18.8%	3.21	1.062	3.77	0.813	3.98	0.780	3.74	0.666	3.50	0.795	3.38	0.831		
		4	4 to 6 years	12	10.3%	3.78	0.936	4.17	1.010	4.31	0.703	3.67	0.853	3.69	0.893	4.19	0.784		
		5	More than 6 years	47	40.2%	3.77	1.172	4.01	1.014	3.98	0.923	3.55	0.809	3.44	1.063	4.04	0.841		
EX1 Total						117	100.0%	3.06	1.389	3.76	0.994	3.91	0.885	3.56	0.741	3.28	1.017	3.52	1.029
VU1	I have the freedom to choose whether or not to use e-tendering applications at my work.	1	Strongly Disagree	26	22.2%	3.31	1.756	3.77	1.130	3.97	0.933	3.51	0.910	3.41	1.209	3.65	1.137		
		2	Disagree	16	13.7%	3.15	1.088	3.52	0.877	4.00	0.584	3.54	0.485	3.08	0.848	3.44	0.717		
		3	Neither Disagree/ nor Agree	26	22.2%	2.63	1.152	3.76	0.798	3.88	0.516	3.41	0.599	3.24	0.758	3.35	0.926		
		4	Agree	27	23.1%	3.14	1.231	3.98	0.653	4.00	0.686	3.68	0.670	3.40	0.746	3.56	0.938		
		5	Strongly Agree	22	18.8%	3.11	1.537	3.67	1.410	3.68	1.438	3.64	0.920	3.17	1.417	3.56	1.327		
VU1 Total						117	100.0%	3.06	1.389	3.76	0.994	3.91	0.885	3.56	0.741	3.28	1.017	3.52	1.029

Table 21. Descriptive statistics table (Source: Excel)

Cronbach's Alpha for Use Behavior	N of Items
0.936	3

Table 22. Reliability Statistics for Use Behavior (Source: SPSS)

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
UB1 "I use e-tendering applications regularly in my procurement activities"	6.0427	7.938	0.876	0.901
UB2 "E-tendering applications are fully integrated into my daily work"	6.2137	7.704	0.896	0.885
UB3 "I utilize all the available features of e-tendering applications"	6.0855	8.251	0.833	0.935

Table 23. Item-Total Statistics for Use Behavior (Source: SPSS)

Cronbach's Alpha for Behavioral Intention	N of Items
0.868	3

Table 24. Reliability Statistics for Behavioral Intention (Source: SPSS)

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
BI1 "I intend to use e-tendering applications in my future procurement activities"	7.6923	3.853	0.705	0.870
BI2 "I will recommend e-tendering applications to peers in the procurement field"	7.4444	4.128	0.817	0.752
BI3 "Assuming I have access to an e-tendering application, I predict that I would use it frequently"	7.4274	4.661	0.746	0.823

Table 25. Item-Total Statistics for Behavioral Intention (Source: SPSS)

Cronbach's Alpha for Performance Expectancy	N of Items
0.875	3

Table 26. Reliability Statistics for Performance Expectancy (Source: SPSS)

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
PE1 "Using e-tendering applications would improve the efficiency of our procurement processes"	7.8376	3.068	0.805	0.780
PE2 "I believe that using e-tendering applications would help minimize errors in our procurement processes"	7.9060	3.655	0.729	0.851
PE3 "Using e-tendering applications would improve the transparency of our procurement processes"	7.7094	3.260	0.749	0.832

Table 27. Item-Total Statistics for Performance Expectancy (Source: SPSS)

Cronbach's Alpha for Effort Expectancy	N of Items
0.704	3

Table 28. Reliability Statistics for Effort Expectancy (Source: SPSS)

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
EE1 "I find e-tendering applications easy to use"	7.2137	2.204	0.604	0.501
EE2 "Learning to operate an e-tendering application would be easy for me"	6.6154	3.032	0.449	0.698
EE3 "E-tendering applications require minimal effort to maintain and update"	7.5043	2.338	0.527	0.609

Table 29. Item-Total Statistics for Effort Expectancy (Source: SPSS)

Cronbach's Alpha for Social Influence	N of Items
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0.789	3
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Table 30. Reliability Statistics for Social Influence (Source: SPSS)

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
SI1 “People whose opinions I value think that I should use e-tendering applications in my work”	6.4701	5.148	0.620	0.732
SI2 “Companies that we regularly do business with use e-tendering applications in their procurement processes”	6.5214	4.717	0.584	0.763
SI3 “My direct supervisor encourages me to use e-tendering applications in my work”	6.6838	3.856	0.705	0.630

Table 31. Item-Total Statistics for Social Influence (Source: SPSS)

Cronbach's Alpha for Facilitating Conditions	N of Items
0.773	3

Table 32. Reliability Statistics for Facilitating Conditions (Source: SPSS)

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
FC1 “My company provides all necessary resources and technical support to facilitate the effective use of e-tendering applications”	6.9915	4.750	0.631	0.668
FC2 “I am well-trained and knowledgeable in using e-tendering applications effectively”	7.2308	4.300	0.608	0.699
FC3 “The company allocates adequate financial resources to ensure the effective implementation and ongoing maintenance of e-tendering applications”	6.8718	5.095	0.591	0.714

Table 33. Item-Total Statistics for Facilitating Conditions (Source: SPSS)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.718	0.516	0.503	0.70477633

Table 34. Regression analysis for Zscore(BI) (Source: SPSS)

Model	Sum of Squares	df	Mean Square	F	Sig.
1 Regression	59.872	3	19.957	40.179	0.000
Residual	56.128	113	0.497		
Total	116.000	116			

Table 35. ANOVA, Dependent Variable: Zscore(BI), Predictors: (Constant), Zscore(SI), Zscore(EI), Zscore(PE) (Source: SPSS)

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
1 (Constant)	-1.012E-013	0.065		0.000	1.000
Zscore(PE)	0.449	0.087	0.449	5.175	0.000
Zscore(EI)	0.018	0.073	0.018	0.250	0.803
Zscore(SI)	0.343	0.082	0.343	4.174	0.000

Table 36. Regression weights estimate (Source: SPSS)

Model	R	R Square		
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			Adjusted R Square	Std. Error of the Estimate
2	0.720	0.518	0.487	0.71617908

Table 37. Regression analysis for Zscore(BI), including interaction terms for Gender (Source: SPSS)

Model	Sum of Squares	df	Mean Square	F	Sig.
2 Regression	60.093	7	8.585	16.737	0.000
Residual	55.907	109	0.513		
Total	116.000	116			

Table 38. ANOVA, Dependent Variable: Zscore(BI), Predictors: (Constant), Zscore(SI), Zscore(EI), Zscore(PE), Zscore(DM1), Zscore(DM1)xZscore(EI), Zscore(DM1)xZscore(PE), Zscore(DM1)xZscore(SI), (Source: SPSS)

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
2 (Constant)	-0.001	0.067		-0.012	0.990
Zscore(PE)	0.459	0.092	0.459	5.000	0.000
Zscore(EI)	0.010	0.077	0.010	0.130	0.897
Zscore(SI)	0.346	0.087	0.346	3.961	0.000
Zscore(DM1)	-0.011	0.067	-0.011	-0.159	0.874
Zscore(DM1)xZscore(PE)	0.006	0.095	0.005	0.059	0.953
Zscore(DM1)xZscore(EI)	0.044	0.075	0.044	0.587	0.558
Zscore(DM1)xZscore(SI)	-0.019	0.087	-0.020	-0.221	0.826

Table 39. Regression weights estimate (Source: SPSS)

Model	R	R Square		
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			Adjusted R Square	Std. Error of the Estimate
2	0.743	0.552	0.523	0.69073000

Table 40. Regression analysis for Zscore(BI), including interaction terms for Age (Source: SPSS)

Model	Sum of Squares	df	Mean Square	F	Sig.
2 Regression	63.995	7	9.142	19.162	0.000
Residual	52.005	109	0.477		
Total	116.000	116			

Table 41. ANOVA, Dependent Variable: Zscore(BI), Predictors: (Constant), Zscore(SI), Zscore(EI), Zscore(PE), Zscore(DM2), Zscore(DM2)xZscore(EI), Zscore(DM2)xZscore(PE), Zscore(DM2)xZscore(SI), (Source: SPSS)

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
2 (Constant)	-0.032	0.065		-0.493	0.623
Zscore(PE)	0.434	0.086	0.434	5.045	0.000
Zscore(EI)	0.050	0.074	0.050	0.667	0.506
Zscore(SI)	0.345	0.082	0.345	4.220	0.000
Zscore(DM2)	0.034	0.066	0.034	0.514	0.608
Zscore(DM2)xZscore(PE)	0.238	0.101	0.237	2.364	0.020
Zscore(DM2)xZscore(EI)	-0.148	0.074	-0.150	-1.998	0.048
Zscore(DM2)xZscore(SI)	-0.067	0.091	-0.067	-0.734	0.465

Table 42. Regression weights estimate (Source: SPSS)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
2	0.745	0.556	0.531	0.68464192

Table 43. Regression analysis for Zscore(BI), including interaction terms for Experience (Source: SPSS)

Model	Sum of Squares	df	Mean Square	F	Sig.
2 Regression	64.439	6	10.740	22.912	0.000
Residual	51.561	110	0.469		
Total	116.000	116			

Table 44. ANOVA, Dependent Variable: Zscore(BI), Predictors: (Constant), Zscore(SI), Zscore(EI), Zscore(PE), Zscore(EX1), Zscore(EX1)xZscore(EI), Zscore(EX1)xZscore(SI), (Source: SPSS)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
2	(Constant)	-0.021	0.066		-0.322	0.748
	Zscore(PE)	0.440	0.085	0.440	5.197	0.000
	Zscore(EI)	0.016	0.075	0.016	0.216	0.829
	Zscore(SI)	0.338	0.086	0.338	3.918	0.000
	Zscore(EX1)	0.165	0.069	0.165	2.378	0.019
	Zscore(EX1)xZscore(EI)	-0.120	0.074	-0.112	-1.631	0.106
	Zscore(EX1)xZscore(SI)	0.090	0.065	0.096	1.383	0.169

Table 45. Regression weights estimate (Source: SPSS)

Model	R	R Square		
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			Adjusted R Square	Std. Error of the Estimate
2	0.728	0.530	0.509	0.70099234

Table 46. Regression analysis for Zscore(BI), including interaction terms for Voluntariness of Use (Source: SPSS)

Model	Sum of Squares	df	Mean Square	F	Sig.
2 Regression	61.456	5	12.291	25.013	0.000
Residual	54.544	111	0.491		
Total	116.000	116			

Table 47. ANOVA, Dependent Variable: Zscore(BI), Predictors: (Constant), Zscore(SI), Zscore(EI), Zscore(PE), Zscore(VU1), Zscore(VU1)xZscore(SI), (Source: SPSS)

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
2 (Constant)	0.003	0.065		0.039	0.969
Zscore(PE)	0.438	0.089	0.438	4.945	0.000
Zscore(EI)	-0.016	0.076	-0.016	-0.210	0.834
Zscore(SI)	0.358	0.083	0.358	4.331	0.000
Zscore(VU1)	0.080	0.066	0.080	1.209	0.229
Zscore(VU1)xZscore(SI)	0.077	0.059	0.092	1.314	0.192

Table 48. Regression weights estimate (Source: SPSS)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.747	0.557	0.550	0.67111908

Table 49. Regression analysis for Zscore(UB) (Source: SPSS)

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	64.654	2	32.327	71.774	0.000
	Residual	51.346	114	0.450		
	Total	116.000	116			

Table 50. ANOVA, Dependent Variable: Zscore(UB), Predictors: (Constant), Zscore(BI), Zscore(FC) (Source: SPSS)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.001E-013	0.062		0.000	1.000
	Zscore(BI)	0.375	0.075	0.375	5.028	0.000
	Zscore(FC)	0.471	0.075	0.471	6.321	0.000

Table 51. Regression weights estimate (Source: SPSS)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
2	0.752	0.565	0.549	0.67120053

Table 52. Regression analysis for Zscore(UB), including interaction term for Age (Source: SPSS)

Model	Sum of Squares	df	Mean Square	F	Sig.
2 Regression	65.543	4	16.386	36.371	0.000
Residual	50.457	112	0.451		
Total	116.000	116			

Table 53. ANOVA, Dependent Variable: Zscore(UB), Predictors: (Constant), Zscore(BI), Zscore(FC), Zscore(DM2), Zscore(DM2)xZscore(FC), (Source: SPSS)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
2	(Constant)	0.003	0.063		0.042	0.966
	Zscore(BI)	0.375	0.075	0.375	5.020	0.000
	Zscore(FC)	0.453	0.076	0.453	5.987	0.000
	Zscore(DM2)	0.089	0.064	0.089	1.396	0.165
	Zscore(DM2)xZscore(FC)	-0.013	0.062	-0.013	-0.214	0.831

Table 54. Regression weights estimate (Source: SPSS)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
2	0.802	0.643	0.630	0.60842294

Table 55. Regression analysis for Zscore(UB), including interaction term for Experience (Source: SPSS)

Model	Sum of Squares	df	Mean Square	F	Sig.
2 Regression	74.540	4	18.635	50.341	0.000
Residual	41.460	112	0.370		
Total	116.000	116			

Table 56. ANOVA, Dependent Variable: Zscore(UB), Predictors: (Constant), Zscore(BI), Zscore(FC), Zscore(EX1), Zscore(EX1)xZscore(FC), (Source: SPSS)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
2	(Constant)	0.009	0.067		0.133	0.894
	Zscore(BI)	0.370	0.068	0.370	5.469	0.000
	Zscore(FC)	0.271	0.078	0.271	3.476	0.001
	Zscore(EX1)	0.352	0.070	0.352	5.026	0.000
	Zscore(EX1)xZscore(FC)	-0.016	0.063	-0.015	-0.249	0.804

Table 57. Regression weights estimate (Source: SPSS)

Appendix B: Questionnaire

- (Q1; DM1) Gender:
 - Male
 - Female
- (Q2; DM2) Age:
 - 24 years old or younger
 - 25 to 34 years old
 - 35 to 44 years old
 - 45 to 54 years old
 - 55 to 64 years old
 - 65 years old or older
- (Q3; DM3) Education Level
 - Primary - Lower Secondary Education Diploma
 - Upper Secondary Education Diploma
 - Post Secondary Education Diploma
 - Higher Education Degree
 - Master's Degree
 - Doctoral Degree
- (Q4; DM4) Position within the Company:
 - Owner
 - Senior Management (C-level, Director)
 - Middle Management (Head of Department, etc.)
 - Experienced Staff
 - Junior Staff
- (Q5; DM5) Business Unit within the Company that your primary responsibilities lie:
 - Procurement/ Supply Chain
 - Information Technology (IT)
 - Administration
 - Human Resources
 - Other (specify_____)
- (Q6; DM6) Sector in which the Company operates:
 - Industry/ Manufacturing
 - Construction
 - Hospitality/ Food Service
 - Retail Trade
 - Transport/ Logistics

- Telecommunications
- Energy
- Financial
- Other (specify_____)
- (Q7; DM7) Size of the Company:
 - Under 50 employees
 - 51 to 250 employees
 - Over 250 employees
- (Q8; DM8) Your role in the decision-making process for digital procurement solutions (e.g. e-tendering applications) at the Company:
 - Lead Decision-Maker
 - Decision Contributor
 - Not involved
- (Q9; EX1) Your experience with e-tendering applications:
 - No experience
 - Less than 1 year
 - 1 to 3 years
 - 4 to 6 years
 - More than 6 years

For the following questions, please select the single response that BEST describes you from the following 5-point Likert scale: 1=Strongly Disagree (SD), 2=Disagree (D), 3=Neither Disagree/nor Agree (NDA), 4=Agree (A), 5=Strongly Agree (SA)

- (Q10; VU1) I have the freedom to choose whether or not to use e-tendering applications at my work.
- (Q11; UB1) I use e-tendering applications regularly in my procurement activities.
- (Q12; UB2) E-tendering applications are fully integrated into my daily work.
- (Q13; UB3) I utilize all the available features of e-tendering applications.
- (Q14; BI1) I intend to use e-tendering applications in my future procurement activities.
- (Q15; BI2) I will recommend e-tendering applications to peers in the procurement field.
- (Q16; BI3) Assuming I have access to an e-tendering application, I predict that I would use it frequently.
- (Q17; PE1) Using e-tendering applications would improve the efficiency of our procurement processes.
- (Q18; PE2) I believe that using e-tendering applications would help minimize errors in our procurement processes.
- (Q19; PE3) Using e-tendering applications would improve the transparency of our procurement processes.

- (Q20; EE1) I find e-tendering applications easy to use.
- (Q21; EE2) Learning to operate an e-tendering application would be easy for me.
- (Q22; EE4) E-tendering applications require minimal effort to maintain and update.
- (Q23; SI1) People whose opinions I value think that I should use e-tendering applications in my work.
- (Q24; SI2) Companies that we regularly do business with use e-tendering applications in their procurement processes.
- (Q25; SI3) My direct supervisor encourages me to use e-tendering applications in my work.
- (Q26; FC1) My company provides all necessary resources and technical support to facilitate the effective use of e-tendering applications.
- (Q27; FC2) I am well-trained and knowledgeable in using e-tendering applications effectively.
- (Q28; FC3) The company allocates adequate financial resources to ensure the effective implementation and ongoing maintenance of e-tendering applications.

Appendix C: Questionnaire (Greek translation)

- (Q1; DM1) Φύλο:
 - Άνδρας
 - Γυναίκα
- (Q2; DM2) Ηλικία:
 - 24 ετών ή μικρότερη
 - 25 έως 34 ετών
 - 35 έως 44 ετών
 - 45 έως 54 ετών
 - 55 έως 64 ετών
 - 65 ετών ή μεγαλύτερη
- (Q3; DM3) Επίπεδο Εκπαίδευσης:
 - Απολυτήριο Δημοτικού - Γυμνασίου
 - Απολυτήριο Λυκείου (ΓΕΛ, ΕΠΑΛ) ή Πτυχίο Επαγγελματικής Σχολής (ΕΠΑΣ, ΤΕΣ)
 - Δίπλωμα/ Πτυχίο Ανώτερης Εκπαίδευσης (Μεταλυκειακό ΕΠΑΛ, ΙΕΚ, κλπ.)
 - Πτυχίο Ανώτατης Εκπαίδευσης (ΑΕΙ, ΤΕΙ, ΑΤΕΙ, ΑΣΠΑΙΤΕ, ΕΑΠ, κλπ.)
 - Μεταπτυχιακό Δίπλωμα Ειδίκευσης
 - Διδακτορικό Δίπλωμα
- (Q4; DM4) Θέση στην Επιχείρηση:
 - Ιδιοκτήτης
 - Ανώτερη Διοίκηση (C-level, Διευθυντής)
 - Μεσαία Διοίκηση (Προϊστάμενος Τμήματος, κλπ.)
 - Έμπειρο Προσωπικό
 - Νέο Προσωπικό
- (Q5; DM5) Τμήμα της Επιχείρησης στο οποίο υπάγονται οι κύριες αρμοδιότητές σας:
 - Προμήθειες/ Εφοδιαστική Αλυσίδα
 - Πληροφορική (IT)
 - Διοίκηση
 - Ανθρώπινο Δυναμικό
 - Άλλο (προσδιορίστε_____)
- (Q6; DM6) Κλάδος στον οποίο δραστηριοποιείται η Επιχείρηση:
 - Βιομηχανία/ Μεταποίηση
 - Κατασκευές
 - Ξενοδοχειακά/ Εστίαση
 - Λιανεμπόριο

- Μεταφορές/ Logistics
- Τηλεπικοινωνίες
- Ενέργεια
- Χρηματοπιστωτικός
- Άλλο (προσδιορίστε_____)
- (Q7; DM7) Μέγεθος της Επιχείρησης:
 - Λιγότερο από 50 εργαζομένους
 - 51 έως 250 εργαζομένους
 - Πάνω από 250 εργαζομένους
- (Q8; DM8) Ο ρόλος σας στη διαδικασία λήψης αποφάσεων για ψηφιακές λύσεις προμηθειών (π.χ. εφαρμογών ηλεκτρονικών διαγωνισμών) στην Επιχείρηση:
 - Υπεύθυνος λήψης αποφάσεων
 - Συνεισφέρω στη λήψη αποφάσεων
 - Δε συνεισφέρω
- (Q9; EX1) Η εμπειρία σας με εφαρμογές ηλεκτρονικών διαγωνισμών:
 - Χωρίς εμπειρία
 - Λιγότερο από 1 έτος
 - 1 έως 3 έτη
 - 4 έως 6 έτη
 - Περισσότερα από 6 έτη

Παρακαλώ δηλώστε το βαθμό συμφωνίας ή διαφωνίας σας στις παρακάτω προτάσεις, με βάση την κλίμακα αξιολόγησης που ακολουθεί: 1=Διαφωνώ Απόλυτα (ΔΑ), 2=Διαφωνώ (Δ), 3=Ούτε Διαφωνώ/ Ούτε Συμφωνώ (ΟΔΣ), 4=Συμφωνώ (Σ), 5=Συμφωνώ Απόλυτα (ΣΑ)

- (Q10; VU1) Έχω την ελευθερία να επιλέξω αν θα χρησιμοποιήσω ή όχι εφαρμογές ηλεκτρονικών διαγωνισμών στην εργασία μου.
- (Q11; UB1) Χρησιμοποιώ τακτικά εφαρμογές ηλεκτρονικών διαγωνισμών σε δραστηριότητές μου σχετικές με προμήθειες.
- (Q12; UB2) Οι εφαρμογές ηλεκτρονικών διαγωνισμών είναι πλήρως ενσωματωμένες στην καθημερινή μου εργασία.
- (Q13; UB3) Χρησιμοποιώ όλες τις διαθέσιμες λειτουργίες μιας εφαρμογής ηλεκτρονικών διαγωνισμών.
- (Q14; BI1) Σκοπεύω να χρησιμοποιήσω εφαρμογές ηλεκτρονικών διαγωνισμών στις μελλοντικές μου δραστηριότητες σχετικές με προμήθειες.
- (Q15; BI2) Θα συνιστούσα εφαρμογές ηλεκτρονικών διαγωνισμών σε συναδέλφους μου στον τομέα των προμηθειών.
- (Q16; BI3) Υποθέτοντας ότι έχω πρόσβαση σε μια εφαρμογή ηλεκτρονικών διαγωνισμών, προβλέπω ότι θα τη χρησιμοποιούσα συχνά.

- (Q17; PE1) Η χρήση εφαρμογών ηλεκτρονικών διαγωνισμών θα βελτιώνει την αποτελεσματικότητα των διαδικασιών προμηθειών μας.
- (Q18; PE2) Πιστεύω ότι η χρήση εφαρμογών ηλεκτρονικών διαγωνισμών θα βοηθούσε στην ελαχιστοποίηση των σφαλμάτων στις διαδικασίες προμηθειών μας.
- (Q19; PE3) Η χρήση εφαρμογών ηλεκτρονικών διαγωνισμών θα βελτιώνει τη διαφάνεια των διαδικασιών προμηθειών μας.
- (Q20; EE1) Θεωρώ ότι οι εφαρμογές ηλεκτρονικών διαγωνισμών είναι εύχρηστες.
- (Q21; EE2) Η εκμάθηση της λειτουργίας μιας εφαρμογής ηλεκτρονικών διαγωνισμών θα ήταν εύκολη για μένα.
- (Q22; EE4) Οι εφαρμογές ηλεκτρονικών διαγωνισμών απαιτούν ελάχιστη προσπάθεια για τη συντήρηση και την ενημέρωσή τους.
- (Q23; SI1) Οι άνθρωποι των οποίων τις απόψεις εκτιμώ πιστεύουν ότι θα πρέπει να χρησιμοποιώ εφαρμογές ηλεκτρονικών διαγωνισμών στην εργασία μου.
- (Q24; SI2) Οι επιχειρήσεις με τις οποίες συνεργαζόμαστε τακτικά χρησιμοποιούν εφαρμογές ηλεκτρονικών διαγωνισμών στις διαδικασίες προμηθειών τους.
- (Q25; SI3) Ο άμεσος προϊστάμενός μου με ενθαρρύνει να χρησιμοποιώ εφαρμογές ηλεκτρονικών διαγωνισμών στην εργασία μου.
- (Q26; FC1) Η Επιχείρησή μου παρέχει όλους τους απαραίτητους πόρους και τεχνική υποστήριξη για να διευκολύνει την αποτελεσματική χρήση των εφαρμογών ηλεκτρονικών διαγωνισμών.
- (Q27; FC2) Είμαι καλά εκπαιδευμένος και με γνώσεις για την αποτελεσματική χρήση εφαρμογών ηλεκτρονικών διαγωνισμών.
- (Q28; FC3) Η Επιχείρησή διαθέτει επαρκείς οικονομικούς πόρους για να εξασφαλίσει την αποτελεσματική εφαρμογή και τη συνεχή συντήρηση των εφαρμογών ηλεκτρονικών διαγωνισμών.

Author's Statement:

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