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THE EFFECT OF ORGANIZATIONAL READINESS FOR CHANGE ON THE USE OF ARTIFICAL INTELLIGENCE: THE CASE OF PUBLIC SECTOR OF AZERBAIJAN.

Master Thesis

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I have written this Master Thesis independently. Any ideas or data taken from other authors or other sources have been fully referenced.

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Abstract

The research studies how the organizational readiness for change effects using and accepting Artificial Intelligence (AI) in Azerbaijan's public sector. The study looks into digital transformation, its roadmap as well as strategies that are involved with it with focus on human factors and AI. It looks at different theories connected to organizational change and technology acceptance such as the Theory of Reasoned Action and Adoption and Diffusion Theory. The research employs a quantitative method in examining the relationship between organizational readiness for change and its use of AI, while taking into account demographic variables as possible influencers. This study makes use of scales to gauge both organizational readiness and AI usage, conducting factor and regression analyses to identify the importance of individual and organizational change motivations as well as capacities on adopting artificial intelligence. The findings propose that AI usage is impacted by both individual and organization readiness, with aspects such as age, gender, education level playing a role in shaping perceptions towards change readiness. These results are in agreement with existing theories. They emphasize the significance of having positive attitudes about technology and an encouraging cultural atmosphere within organizations for effective integration of AI.

Keywords: organization readiness for change, use of Artificial Intelligence, regression analyses.

1. Introduction

The First Industrial Revolution, the beginning of the Industrial Revolutions, emerged in England. It is the revolution that first spread to continental Europe and then to the whole world, replacing tooled production with machine production and workshop production with factory production. The First Industrial Revolution reveals the dual class structure. It also resulted in making growth possible for economies as a result of the First Industrial Revolution (Crafts, 1996). From the beginning of the Industrial Revolution until today, there appear to be three basic stages of great increase in industrial productivity. Machines powered by steam power began to appear in factories towards the end of the 18th century. Mass production with electrical energy was seen at the beginning of the 20th century. It is seen that the use of automation in industry, along with electronics and information technologies (IT), has increased since the 1970s. The First Industrial Revolution, which we saw in the period between 1760 and 1830, began to have an impact in England with the mechanization of weaving looms. In line with this scope, it seems that the use of coal and steam instead of wood and the increase of motive power resulted in mechanization and moving production to factories. After the light industry such as textile, the First Industrial Revolution also affected the heavy industry with the emergence of technological developments and the increase in knowledge on production (Siemens, 2016).

It was implemented in Henry Ford's automobile factory and was used during World War II. With the era of mass production that was widespread in the post-World War II period (with the influence of Keynesian spending policies), the beginning of the Industrial Revolution occurred. This period is defined as Fordism. An important feature of the production in this period is the sliding belt system. Thanks to this system, mass production based on a single type was possible. Countries used the mass production system of Fordism as the main strategy in their production. This situation was adopted until the late 60s (Pietrykowski, 1995).

With the diversity in consumer preferences and the increase in competition, the single-pattern production offered by Fordism began to have difficulties and this system collapsed at the end of the 1973 oil crisis (Pietrykowski, 1995).

The time period, which has been in effect since the 1970s, is known as the Third Industrial Revolution. Automation in production was achieved after Second World War with development of electronics and information communication technology (ICT). The automation process of production has advanced to next stages as a result of developing programmable

PLCs. The First Industrial Revolution was marked by the mechanization of production, followed by the Second Industrial Revolution with the serialization of production. Then came the Third Industrial Revolution which saw automation and digitization in producing process. Now we are seeing a new stage called Fourth them where added things like cyber-physical systems, Internet of Things and Services as well as Artificial Intelligence (Siemens, 2016).

The first studies in the field of artificial intelligence were based on the idea of creating machines that could imitate human intelligence, and the first claims that artificial intelligence could imitate human intelligence were made in the 1960s. At today's stage, we are talking about the existence of systems that can imitate human intelligence, perform single tasks given to them and various tasks according to their level of development, and self-learn in line with the data they obtain, and artificial intelligence has become an interdisciplinary field of study that affects individuals, brands, institutions, and states. And in this respect, it can be said that it has the power to influence all functions in an institution. In this sense, the first striking effect of artificial intelligence technologies, as Lansiti and Lakhani (2020) state, is on changing the structure of organizations, shaping the world around us, and “the things we do” rather than imitating human nature.

We are witnessing an unprecedented change and transformation as artificial intelligence systems penetrate the fabric of institutions and change the functioning of sectors. Change continues at such a rapid pace that almost everyone will have artificial intelligence experience, artificial intelligence applications; It spreads to many areas, from transportation to production, from health to education, from law to communication. The field of public relations also has its share of this change that covers a wide area. Because, in a period where changes and transformations are experienced so rapidly, it is seen as a necessity for the discipline of public relations, whose main source is people and communication, to adapt to the conditions of the digital age. As a matter of fact, increasing the efficiency of public relations practices through the use of artificial intelligence applications emerges as an important trend in the development of public relations. In this sense, it becomes possible to redefine artificial intelligence within the framework of public relations; Artificial intelligence is defined by Galloway and Swiatek (Galloway & Swiatek, 2018) as "technologies that undertake public relations activities by imitating human cognitive abilities and perform human functions under the control of public relations practitioners or independently of them."

Nowadays, in public relations processes, "machine learning", "deep learning", "natural language processing (NLP)", "chatbot" or "artificial intelligence-supported services, technologies, and applications" are starting to be used. Thus, public relations experts also have the opportunity to use these applications as a tool. In this context, artificial intelligence applications, which have a new adaptability and contextualization for public relations, are gaining importance with both the usage areas they create, the methods and norms they create, and a series of technological and relational implications they bring.

It is stated that it is critical for organizations to manage their workforce profiles as there are changes in workforce profiles as a result of the changes brought by Industry 4.0. As manual work has become standard thanks to robots and workforce competencies have changed, the need to update the training plans of businesses has emerged. As robots are used in more organizations, there is a need to analyze the data that will be generated. With the emergence of Artificial Intelligence, businesses need to provide resources to competent workforce profiles and work to improve the competencies of existing workforce profiles.

The purpose of the study is to investigate how organizational readiness for change affects the acceptance and utilization of Artificial Intelligence (AI) within public administration in Azerbaijan. This research aims at understanding what factors, including individual as well as group motivation towards alteration along with capacity to change on an organizational level, influence successful implementation and usage rates for AI technologies. Further, it looks into if demographic variables such as gender, age and educational status have any relation with readiness for change within organizations and then adopting these new AI methods or not. The research makes use of a quantitative method, using a conceptual model to examine the relationship between organizational readiness and AI adoption.

Research Questions:

What is the impact of organizational readiness for change on the adoption and use of Artificial Intelligence in the Public Sector Organization of Azerbaijan?

a) ***Does the organizational readiness for change differ according to demographic variables?***
b) ***Does the adoption and use of Artificial Intelligence differ according to demographic variables?***

2. Literature Review

2.1 Digital Transformation

Over the last 50 years, information technology (IT) organizations have profoundly transformed businesses and reshaped their competition. Currently, organizations are at the center of an IT-focused transformation and competition. As the importance of IT within organizations increases, opinions have increased that the IT strategy of organizations should be compatible with their overall business strategy. When the impact of IT on organizations is examined chronologically, three waves can be mentioned. The first wave, covering the 1960s and 1970s, was related to process automation. This wave led to the automation of individual activities such as order processing, enterprise resource planning on computer systems, and bill payments. Thus, the data generated by each activity was stored, analyzed, and productivity increased. With the rise of the Internet in the 1990s and 2000s, the second wave of IT transformation occurred, paving the way for globalization and close integration with globally dispersed partners, customers, and suppliers. The third IT wave is the digital transformation we are currently experiencing. Digital technologies, in which IT has become a part of smart and interconnected products with software, processors, and sensors, have given birth to digital transformation. Internet of Things, artificial intelligence, big data analytics, machine learning, cloud systems, robotics, social media, wearable technologies, etc. technologies have driven digital transformation and resulted in dramatic improvements in product performance (Gupta 2018, p. 9).

These technologies transcend industry boundaries, disrupt existing value chains and business models in industrial enterprises, introduce a new wave of innovation, change organizational structures, transform the way we do business, and offer a new service model with many options for the customer. It is assumed that digital transformation will lead organizations to economic growth, and only organizations that position themselves correctly and develop strategies to capture the benefits of digital transformation will successfully pass the third wave of transformation (Gupta 2018, p. 10). What is Digital Transformation?

Although digital transformation is one of the most frequently encountered and used terms in the business world recently, it can be interpreted differently by everyone. While some interpret digital transformation as the transformation of business processes as a result of the digitizing world, where every innovation and transformation is supported by new technologies, others see it as the changes in business practices after the fourth industrial revolution. Some interpret it as improvements in more specific technological developments, such as the automation of production processes and growth with new customer channels (Westerman et al., 2011).

One of the most comprehensive descriptions of digital transformation was included in the IBM Institute for Business Value published in 2011. Digital transformation is a result and focal point of the internet and globalization, and it has been stated that business models have undergone digital transformation with the emergence of digital products and online commerce powered by the mobile revolution, social media, and big data. According to IBM's approach, for a business to be successful in the digital transformation process, it must integrate digital capabilities into daily operations as well as redesign customer evaluation. Microsoft has defined digital transformation as the radical change of traditional processes, products, and services by applying new technologies, data-based, interconnected, providing completely new business models and efficiency gains.

Although it is not easy to define digital transformation in a way that suits all businesses and processes, digital transformation can be described as the integration of digital technologies into all business processes and, as a result, comprehensive changes in the way of doing business. In addition, digital transformation can also be interpreted as a cultural change that requires businesses to constantly challenge the status quo, experiment differently, and not be afraid of making mistakes.

Industry 4.0 and the Process of Digital Transformation

The term Industry 4.0, also referred to as industries of the future, connected factories, and smart factories, pertains to the Fourth Industrial Revolution, which gained prominence with the advent of the steam engine, production lines, and automation. In his study, Shi et al. (2020, p. 90) defined the concept of Industry 4.0, synonymous with the Fourth Industrial Revolution, as the integration of cyber-physical systems, the concept of the Internet of Things, and cloud computing systems into manufacturing technologies, particularly in the realms of automation and data exchange, to establish structures characterized as smart factories.

With this revolution, new technologies have been integrated into industrial processes to enhance safety, performance, and energy efficiency while reducing labor costs. Digital innovations in the industry in the 21st century have led to the simultaneous use of terms Industry 4.0 and digital transformation (Schulthess 2018).

Technologies such as robots, machine learning, the Internet of Things (IoT), cloud computing, and artificial intelligence have brought about and continue to drive significant change in the business world.

These technologies, which offer affordability with their decreasing costs, are now accessible to businesses of all sizes. The Fourth Industrial Revolution has opened up boundless opportunities for businesses, presenting them with a plethora of technological options. Throughout this process, businesses have had to address numerous questions, such as which technologies align with their organizational needs, where they should invest, and how they will allocate resources to these technologies. Beyond the selection of technologies, it has become evident that the institution's strategy, capabilities, business models, and even organizational structure must be compatible.

Choosing, implementing, and utilizing these Industry 4.0 technologies suitable for the institution necessitates a transformative process that impacts all facets and resources of the enterprise (Hanley et al. 2018). In this regard, digital transformation essentially outlines the strategy and roadmap that businesses must adopt to transition into the Industry 4.0 era.

In his opening speech at the 2016 World Economic Forum summit, Klaus Schwab stated that the most important features that distinguish the fourth industrial revolution from others are its speed, holistic systematic impact, and depth. Dördündü stated that the industrial revolution has a feature that increases exponentially, changes, and changes, and that it has the feature of connecting a large number of people, systems, and objects with each other simultaneously. According to Schwab, accessing and transferring information is very easy and fast, and processing power, information storage capacity, and information access potential reach unlimited levels.

While digital transformation and the fourth industrial revolution create many opportunities for institutions and people, they have transformative effects on society, such as increasing income inequality and unemployment triggered by technology destroying the jobs people do. As the physical, social, biological, and digital worlds come closer to each other, new problems such as cybersecurity, information privacy, or biological weapons emerge. In this process where states, institutions, and people transform, those who can produce solutions to different situations, have high creativity, and can use information and technology will have a higher chance of continuing in this order than those who cannot achieve these.

In this period when Industry 4.0 is now on everyone's agenda, taking into account its effects on society and especially on employment, and its effects on human life have also begun to be emphasized.

The world is fighting against challenges on a global scale such as depletion of natural resources, global warming, increasing economic inequality, and terrorism. We are experiencing an age of uncertainty in which complexity increases in many areas. In order to solve social problems, information technologies should be used in the best way by establishing connections between people and objects, real and cyber worlds (Fukuyama, 2018). Digital transformation should also be used to develop strategies to create better lives for people and maintain healthy economic growth.

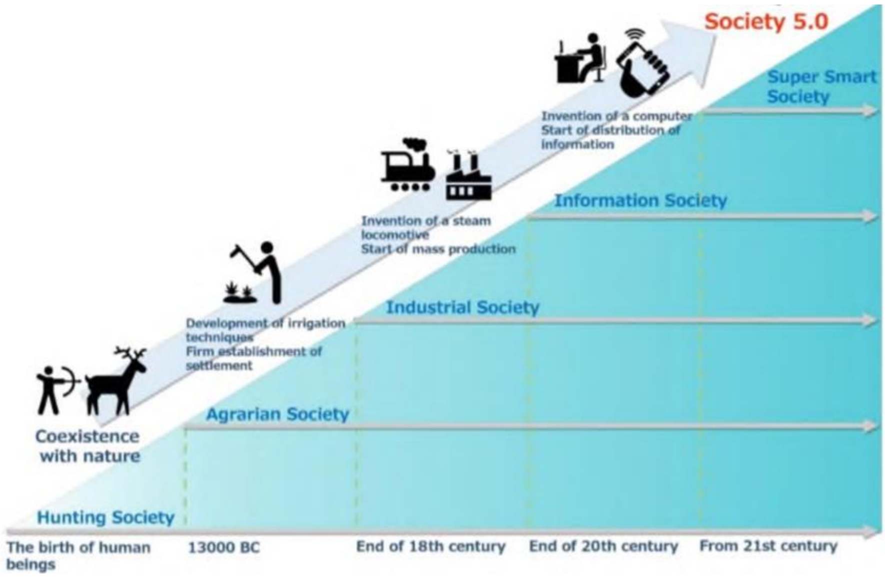
Japan's government is grappling with falling birth rates and an aging population, as well as a shrinking workforce and rising social security costs. In addition, increasing environmental pollution and natural disasters are listed as other problems that need to be dealt with in Japan. Japan is working on a super smart society strategy to deal with these problems. To achieve this goal, it created the Society 5.0 philosophy.

The term Society 5.0 was introduced at the Japan Science, Technology, and Innovation Council in January 2016. It was used in the “Fifth Science and Technology Basic Plan”. However, this term was used in 2017 at the CeBIT fair held in Hannover, Germany, Japanese Prime Minister Shinzo Abe explained the Society 5.0 philosophy as "Technology should be perceived by societies as a helper, not as a threat." When he introduced it by saying, it attracted the attention of the world.

While the concept of digital transformation is generally used for businesses and the business world, it also affects governments, state institutions, and organizations working with it. Therefore, with Society 5.0, Japan aims to address various social challenges by incorporating the innovations of the fourth industrial revolution (such as the Internet of Things (IoT), big data, artificial intelligence (AI), robots, and the sharing economy) into all sectors and social life. It aims to create a society where problems can be resolved. With this philosophy, Japan wants to establish an order in the society of the future where new values and services are constantly created and people's lives are made more sustainable and harmonious (Fukuyama, 2018).

Just as Industry 4.0 describes the fourth industrial revolution, Society 5.0 is stated as the fifth of the social stages that humans go through. As seen in Figure 1, these stages are respectively: hunting society, agricultural society, industrial society, information society. (Fukuyama 2018).

Figure 1. The Evolution of the Society 5.0 Concept.



As the Japanese government proposes the super smart society or Society 5.0 strategy, policy, and even philosophy, the four main goals set against the main problems identified by Keidanren (2016), the Japan Business Federation, are listed below:

a) A smart society that is not harmed despite the decrease in population
b) A society in which the aging population and women can actively participate
c) A secure society in both cyber and physical areas
d) A society contributing to the solution of global environmental problems

Roadmap of Digital Transformation

In the 1990s, businesses invested heavily in new technologies and thus managed to stay ahead of their competitors. However, today, businesses have to be much more selective due to both economic constraints and the diversity of technologies (Andal-Ancion et al., 2003).
By analyzing their internal processes and determining their strategies, businesses should invest in the right technologies. In this system where technology alone is not enough, businesses must also support their technologies with their own processes, human resources, and strategies. For this reason, the term technological investment is now being replaced by the concept of digital transformation. Not only innovation or investment in a single field, but the business as a whole needs to transform towards digitalization. Many consultancy companies have created roadmaps

to assist businesses in this process, and institutions have shared documents for this purpose. As can be seen from here, there is no one-size-fits-all roadmap for digital transformation. The path each business will follow will be unique, and for digital transformation, businesses must follow a method suitable for their own processes. Two resources that can be referenced in the digital transformation journey are listed below.

Microsoft has identified 4 basic topics that can be followed in its digital transformation journey:

1. Deepening customer interaction (Engage your customers) – Increasing customer interaction by providing personalized, enriched, and connected experiences.
2. Empower your employees - Enabling employees to achieve more by creating a smart, flexible, and safe modern working environment.
3. Optimize your operations - By increasing the flow of information in all business operations, synchronizing business processes, and connecting them with the supply chain, improving interaction with.
4. Transform your products – Gathering information about the use of products, designing innovative features, and forming teams to develop products.

When you examine the content titled many different digital transformation roadmaps, you will see that similar titles are listed. In this study, the "human" factor in digital transformation roadmaps will be discussed, and a method will be suggested to understand where employees are in this process.

Digital Transformation Strategy

Digital transformation strategy, like digital transformation, is one of the concepts that are frequently mentioned but cannot be easily agreed upon. It is generally accepted that the IT department has strategies, the marketing department has social media and mobile strategies, or the R&D department has new product development strategies, indicating that the business has a digital transformation strategy. However, research shows that digital transformation strategies are the transformation strategy of not only a department but also the entire enterprise. Here, it is important to understand the difference between traditional business strategies and the digital transformation strategies that are on the agenda today. The difference between traditional business strategies and digital transformation strategies of businesses is shown in Table 1.

Table 1. Traditional Vs. Digital Transformation Strategies.

	Traditional Organizational Strategy	**Digital Transformation Strategy**
Focus Point	Optimization of individual technologies and individual units	Focusing on the implications for products, services and business models as a whole
Scope	Detailed content of the strategy	How to realize the organizational vision
Aim	Operational efficiency	Transformation of work, re-planning customer experience, operations and business models
Time Interval	Few years	Constantly
Source of Innovation	Talented individuals and competencies within the organization	Collaborative: sharing effort and knowledge across sectors and different business units
Business Model Cycle	Slow to average speed	Fast-paced
Method	Predict and plan	Experience and respond
Business Model	Service provider, asset creator	Creating technology and synchronizing networks
Competitive Advantage	Registered assets	Ability to transform and adapt

Source: Mäkinen, T., (2017). Strategizing for Digital Transformation: A Case Study of Digital Transformation Process in the Construction Industry.

According to Mark McDonald, digital strategies do not approach technology in isolation but design how digital technologies can transform the business' relationships with its customers, employees, and the entire market. Digital strategies enable digital information and physical resources to combine to create new value and income (Gobble, 2018, p. 66).

A survey conducted with a US management expert also confirmed that a successful digital transformation is related to strategy, culture, and talent development rather than technology-related issues (Sawy et al., 2016).

Unlike traditional strategies built on organizational capabilities, a digital strategy should define a future vision and reinterpret business and commerce. For a successful digital transformation, the focus should be on how the transformation will occur rather than the actual content of the change. In most strategy research, digital transformation is defined not as the implementation of new technologies in business but as the development of digital strategies to benefit from the possible advantages of new technologies. It has been stated that new technologies will not offer a sustainable competitive advantage unless they are applied specifically to the business, but the lack of a digital strategy will be the biggest obstacle to digital transformation (Mäkinen, 2017).

With the digital transformation process, businesses that want to reach digital maturity encounter many problems. However, when looking at these problems, the company's lack of a digital transformation strategy is seen as the biggest obstacle. According to analysis of digitally mature businesses, digitally mature businesses are five times more likely to have a clear digital strategy than businesses in the early stages of digital transformation. Businesses that have reached digital maturity are also more likely to have a collaborative culture that encourages risk-taking (Kane et al., 2015).

In this environment, where business models are shorter-lived and operating models need to be constantly reconsidered, a consistent digital transformation strategy supported by management becomes important. Business leaders must stay one step ahead of changing business models and constantly redesign customer experience, operational processes, and new business models. Therefore, the key element of a good digital transformation strategy is not a roadmap to achieve the desired state or best organizational practices. A good digital transformation strategy needs to focus on driving innovations in the business's products and operations, as well as continuous improvement in its business and value creation models (Mäkinen, 2017).

The challenge of completely transforming a business can often be met with a strong, coherent, and comprehensive vision at the heart of a good digital strategy. One of the most driving forces behind digital transformation is the top management vision that emphasizes the importance of the digital transformation strategy. In a study conducted in 2013, in businesses where senior management supported digital transformation, 93 percent of employees agreed that the issue was important (Fitzgerald et al., 2013). A consistent perception of digital vision supported by senior management within the organization also increases collaborative activities within the work environment, as employees share a common goal and purpose on the subject. Collaboration within the business also reveals innovations (Mäkinen, 2017).

Merely creating a foundation for digital innovations has not been deemed sufficient in itself; because a digital strategy must monitor, evaluate digital transformation initiatives, and consistently test their impact. In addition, responsibilities should be determined in the planning and implementation of digital transformation projects. In digital transformation applications where responsibilities are determined and cooperation between teams is ensured, teams can receive the organizational support they need to implement transformative change. Units working with traditional methods may see teams working in the new digital business model as a threat and enter into a conflict of interest. The digital transformation strategy should support and coordinate the communications of new digital units and units working with traditional methods (Westerman et al., 2011).

After testing and evaluating digital transformation initiatives, it must be ensured that these initiatives have sufficient resources such as money and time. At the same time, since these initiatives affect the entire organization in both creating and gaining value, the initiatives must have sufficient IT infrastructure. According to Drnevich and Croson (2013), these investments in IT infrastructure can often be overlooked because monetary returns can rarely be directly allocated to IT infrastructure and information resources.

Although digital strategies are specific to businesses and do not have a definitive recipe, there are some accepted methods. First of all, the digital world is changing very quickly, and businesses need to be flexible in their organizational structure, technology, and personnel to keep up with this. It is expected that old organizational hierarchies will be abandoned, and agile organizations that can quickly adapt to new technologies will be established. Digital transformation also requires taking risks. For a successful strategy, businesses need to establish a structure that encourages risk-taking and supports independence. Finally, businesses need to increase cooperation between units and overcome corporate resistance to digital transformation (Gobble, 2018, p. 66).

Digital Culture

The culture of a business is a result of how the business operates and functions. Business culture consists of the sum of what the employees of the company believe in, what they value, and the experiences of the employees. Having a culture that empowers employees and gives them a sense of purpose has become very important for businesses (Buvat et al., 2017). Digital culture refers to the culture shaped by the emergence and use of digital technologies. Digital technologies have become so integrated into the processes of businesses that digital culture studies cover not only technology-related studies but all the activities of the business (Miller, 2011).

Without establishing a strong foundation for business culture and aligning employees with a digital vision, it is extremely difficult to make meaningful progress in digital transformations. Ian Rogers, chief digital officer of LVMH, stated that the most important moment for a business is to embrace the fact that digital transformation is not a technological issue but a cultural change. It has also been emphasized that cultural change is a prerequisite for digital transformation (Buvat et al., 2017).

According to research conducted by MIT Sloan and CapGemini consultancy company, digital culture is defined as the combination of seven basic features. The first of these is stated as innovation. Innovation is defined as the prevalence of behaviors that support risk-taking, disruptive thinking (thinking about changing the existing order), and the search for new ideas (Buvat et al., 2017).

Digitally mature businesses are more inclined to take risks. Companies that have reached less digital maturity see the fear of risk in their businesses as a major deficiency (Kane et al., 2015). Phil Simon, who studies the impact of technology on businesses, sees risk aversion as a serious obstacle that plagues many well-established institutions. For example, he states that companies such as Facebook, Amazon, or Google, which are considered very successful, take serious risks, but despite this, many businesses still do not leave the area they consider safe. Cisco general manager John Chambers stated that their company started working on the Internet of Things seven years ago, although the market was not yet ready for it. However, he added that he has the courage to continue his business without excessive investment.

It would not be correct to say that avoiding risk is a mistake experienced only by leaders. Employees are as afraid of taking risks as their managers. It is especially important to encourage employees to take risks in the digital transformation process, and businesses need to take action towards this. The second of the seven basic features that make up digital culture is data-based decision-making, that is, ensuring more accurate decisions are made by using data and analytical systems. Organizational culture should support the use of data and analytics in decision-making processes (Buvat et al., 2017). Recent studies have found that social data has also begun to influence decisions and operational processes. For example, Twitter is expanding its scope from being just a social media platform to a provider of social and mobile analytics data. In 2014, Twitter acquired the social data aggregator Gnip in order to simultaneously include mobile data in its business intelligence systems (Kane et al., 2015).

The third feature of digital culture is collaboration. To create a digital culture, businesses should increase their capabilities by forming inter-departmental and cross-functional teams. People often think that innovations occur when a few talented individuals suddenly conceive them (Buvat et al., 2017). In reality, many new ideas emerge through the collaboration of people with diverse backgrounds and abilities. Companies that have achieved digital maturity recognize the benefits of collaboration. Eighty percent of employees at such companies state that their work environments support collaboration more than those of their competitors.

Companies with digital maturity often utilize cross-functional teams to implement new digital initiatives (Kane et al., 2015).

An open culture is the fourth feature of digital culture. Businesses need to enhance their collaboration with external partners such as suppliers or customers. A shared culture should be cultivated, encompassing third-party relationships like suppliers and customers, and a common culture should be fostered through open communication as much as possible (Buvat et al., 2017).

Prioritizing digital (Digital-first mindset) is another feature of digital culture. Prioritizing digital means seeking solutions using digital technologies as much as possible when approaching a new opportunity or problem (Buvat et al., 2017). The digital world is utilized for accessing information and conducting transactions, ranging from business information systems to internet banking, from online commerce to government services. With the expansion of the digital realm at this stage, businesses should proceed by considering digital products when designing new processes or seeking new solutions. Although traditional channels are not entirely abandoned, evaluating digital solutions as the primary option is crucial in fostering a digital culture (Wilson, 2018).

Agility and flexibility, defined as the speed and dynamism of the decision-making process and the organization's ability to adapt to changing demands and technologies, are characteristics of digital culture (Buvat et al., 2017). Agility refers to the business's capacity to swiftly adapt to changes. Flexibility involves performing various tasks within businesses by acquiring new equipment with existing resources, training employees to perform multiple roles, or hiring resources capable of fulfilling diverse tasks (Kelley, 2016). Perry Hewitt, the digital director at Harvard University, emphasized that agility and flexibility are more vital than technological capabilities. It is asserted that the twenty-first century revolves around agility, adaptability, and the creation of new opportunities (Kane et al., 2015).

Customer centricity is the last of the digital culture characteristics. Customer centricity can be described as the use of digital solutions to expand the customer base, transform the customer experience, and create new products (Buvat et al., 2017). Customer centricity not only provides great service to the customer but also aims to provide a good experience to the customer, starting from the awareness process and including sales and after-sales processes. By putting the customer at the center of the business, it is necessary to collect the customer's data through Customer Relationship Management systems and see the customer 360 degrees. In this way, the customer experience can be improved. Customer centricity does not only include the sales and customer relations departments within the business, but the processes from the customer should be transferred to the entire business. According to research, companies that make customer centricity a strategy are 60 percent more profitable than companies that do not make it a strategy (Macdonald, 2019).

Establishing a digital culture within the organization plays a critical role in digital transformation, and businesses are actively working on it. However, difficulties are encountered in the formation of a digital culture. The reasons for these challenges can be stated as leaders neglecting, underestimating, or misunderstanding the importance of culture in digital transformation strategies. Another reason is that the existing business culture is deeply entrenched, making it difficult to effect change. Employees, as well as customers, are becoming increasingly digital day by day. A lack of resistance to digitalization among business leaders is another factor preventing the development of a digital culture. Most behavior change initiatives fail because employees are not empowered to acquire new skills, nor are they encouraged to learn new expertise and create new models (Buvat et al., 2017).

Digital technologies can bring new value, but businesses can only access these benefits if they have a deeply ingrained and established digital culture. Businesses need to initiate this process with a clearly articulated vision, and their leaders must actively support this endeavor. Businesses that invest in their people and align the company's values and mission with their employees are laying the groundwork for successful digital transformation.

In this way, they can create an ecosystem where learning, experience, and growth are supported. Employees also unite to achieve greater returns rather than just individual gains. If businesses plan early and implement clear and purposeful practices, they can transform their digital culture identity into a significant competitive advantage (Buvat et al., 2017).

Human in Digital Transformation

With digitalization in business life, many businesses have become more easily able to access technologies such as wearable sensors, eye scanning, 3D printers, drones, and virtual assistants. With these technologies, jobs are also transforming, and old jobs are being replaced by new tasks brought by new technologies. Developments such as driverless cars, self-service technologies, and robots performing surgery will replace the people who currently hold these positions (Ford, 2015).

According to the World Economic Forum's predictions, five million jobs will disappear by 2020 due to world-changing technologies such as artificial intelligence, robots, and nanotechnology. Some jobs will quickly evolve into different tasks, requiring people to quickly acquire new skills and keep up with the process (Sousa and Rocha, 2019, p. 328). Businesses are expected to constantly seek the right personnel according to emerging new talent needs. According to Microsoft's report, there may be a shortage of forty million highly skilled personnel by 2020. Eighty percent of businesses agree that current employee skills differ from future talent needs. According to research, 83 percent of jobs will be transformed within three years, so businesses should develop strategies to prepare their employees for the future and ensure their involvement in new technologies.

According to research conducted by Microsoft, the most significant challenges encountered in digital transformation are the lack of resources and talent, with the second being the resistance of business culture to transformation. This information comes from Digital by CCL and CorporateLeaders (2018).

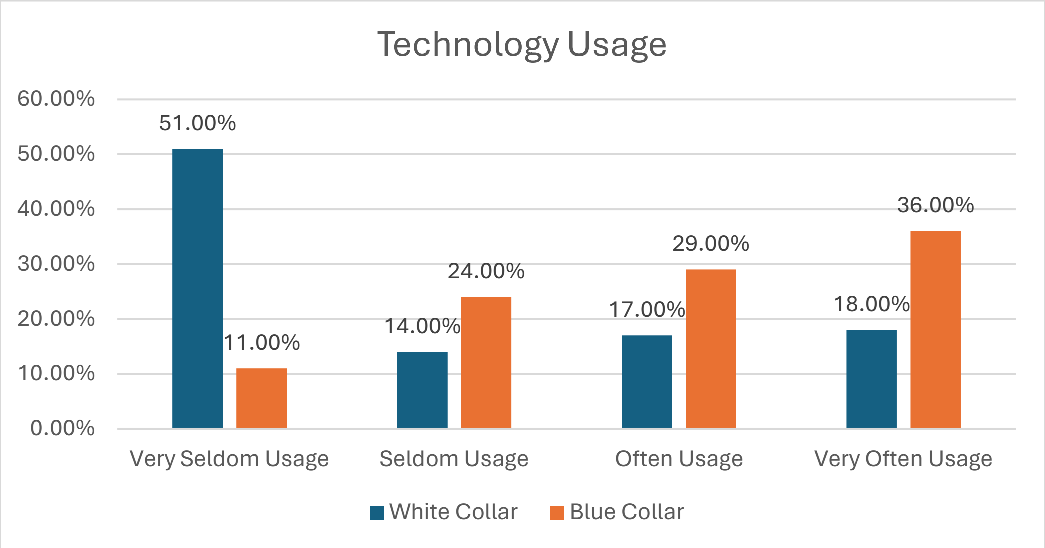
According to the Transformation Readiness Survey Summary report, the primary difficulties encountered in digital transformation are insufficient skills within the business, followed by the lack of a clear vision for digital transformation, challenges in integrating new technologies, and resistance to transformation. As supported by these studies, increasing personnel skills and addressing resistance by involving them in the digital transformation process are crucial aspects of successful digital transformation.

One of the most critical factors in implementing and determining digital transformation strategies in businesses is their employees. Employees are the most affected by the transformations that businesses undergo. With the cultural and systemic changes that businesses encounter during digital transformation, it is vital to include employees in the process. As professions are predicted to evolve in the future and finding needed talents may become challenging, businesses must develop strategies to maximize the benefit from their existing personnel. The more employees are involved in the process and engaged in digitalization, the more they will adapt and contribute to both the business and their own future success.

Resistance will definitely be one of the challenges faced by businesses in the process of transformation and preparing employees for the technology it triggers. Resistance to change is a natural and expected reaction of every human being. In fact, a lack of resistance may mean that employees in the organization do not believe that change will occur or that they believe it will not affect them. Both the absence and presence of resistance are issues that organizations need to examine. Correctly identifying resistance and guiding employees appropriately play a critical role in the transformation process (Gupta, 2018, p. 23).

While businesses are changing the way they operate with digital technologies, the fact that digital technologies are part of daily life, independent of business life, contributes to the transformation process. This is because, in addition to the technology employees use in business life, they also constantly use technology in their daily lives as consumers. Employees regularly utilize technologies such as online banking, social media, and online shopping in their daily lives. However, engagement with this technology needs to be incorporated into business life to a greater extent. This is particularly true for blue-collar workers who engage in more manual labor. Although it is believed that they do not need technology due to the nature of their jobs, it is predicted that with evolving job roles, both white-collar and blue-collar employees will increasingly use technology in every aspect of their work. Figure 2 illustrates the technology usage rates of blue-collar and white-collar employees.

Figure 2. Technology Usage Levels by Employee Types.



Source: Deloitte (2017)

With the introduction of technologies such as robots, the Internet of Things, and artificial intelligence into business life, businesses need to revise the competencies of their staff and enable them to work alongside robots or autonomous software. While it has been determined that 24 percent of blue-collar employees think that technology is unimportant in business life, it will be crucial for businesses to assess their employees and prepare them for future technologies.

To emphasize the importance of employees in this process and to ensure that they possess the skills required for the future, businesses need to formulate the right strategies and conduct accurate analyses. Understanding whether employees are ready for technology and the resistance they display, analyzing the distribution of employees' receptiveness to technology, and gauging how digital transformation strategies are perceived will be beneficial in developing an effective strategy. Technology and digital transformation initiatives that employees do not embrace will not yield added value.

Artificial Intelligence

Artificial Intelligence (AI) is a powerful force that has begun to impact many fields, leading to increased academic interest in comprehending its effects and possibilities. The central idea of AI involves machines being able to carry out tasks requiring human intelligence. These duties include a wide range from learning and reasoning to solving problems, perceiving things and understanding language among others.

Enholm et al. (2022) discuss how artificial intelligence (AI) technologies add value to businesses and cover key things that aid or hinder the utilization of AI, distinct types of AI within groups and organizations, along with primary and secondary results resulting from utilizing this technology. The study underlines how AI is crucial in strategy for demonstrating competitive advantages, as well as revealing hurdles encountered by companies trying to utilize their AI ability to the fullest. The work of Dang Minh et al. (2022) concentrates on explainable AI (XAI), aiming at explaining the decision-making process of AI and promoting transparency and trust. The main reason for developing XAI, or Explainable AI, is to tackle the 'black-box' attribute of many artificial intelligence systems, where it can be difficult to understand why certain choices were made as the reasoning behind them stays unclear. Without the clear explanation, it's hard for people to hold these AI accountable and understand their actions and decisions fully.

This is a field that scholars are becoming more interested in, and we can see this from the rising number of writings about AI being used by public organizations. These writings explore how it's adopted, its effect, and problems faced when these groups use AI. Neumann, Guirguis and Steiner (2024), they conduct a comparative case study on eight Swiss public organizations using the technology-organization-environment framework to examine factors influencing adoption of AI. The findings they made, it displays that technological and organizational components have varying importance based on a firm's phase in the procedure while environmental aspects are usually of lesser significance. Neumann et al. (2024) wrote an article about their work - they study with eight Government Bodies from Switzerland who use this Framework: Technology-Organization-Environment or TOE Model to analyze what makes them take up artificial intelligence? They find out that parts related to technique change their

value based on the stage during the process; those company-related might not always be a big part, while ones connected with environment usually hold less significant position overall.
Application of Artificial Intelligence has seen increasing amount of published materials delving deeply into the acceptability, impact, and challenges of integrating artificial intelligence within these kinds of settings, public organizations have become a subject that students are becoming more interested in recent days. Nemenman et al., address their assignment in-depth in their paper "Comparative Analysis For Adoption Factors."
In order for AI to be successfully used by public health organizations, Fisher and Rosella (2022) have identified six key priorities: modern data governance; investment in updated data and analytic infrastructure; addressing the skills gap; formation of strategic collaborative partnerships; good AI practice for transparency and reproducibility; and explicit consideration of equity and bias.

2.2 Organizational Readiness for Change

Organizational readiness encompasses an organization's psychological and behavioral preparedness to implement change and the collective mindset and commitment of an organization's members towards the change initiative, as well as their belief in the collective capability to execute the change effectively (Weeks et al., 2004, pp. 7-8). When considering organizational readiness for change specifically in the context of accepting technology, it refers to the organization's overall preparedness, both culturally and operationally, to integrate new technological solutions into its existing systems and processes, which includes the willingness and ability of the organization's members to adapt to technological advancements, the alignment of the new technology with the organization's strategic goals, and the presence of adequate resources and infrastructure to support the technology adoption. Organizational readiness for technological change is critical as it can significantly influence the success rate of the technology's implementation and the realization of its intended benefits (Weiner, 2009).

Technological innovations that emerge with digital transformation change the structures and technologies of organizations, as well as the way they provide service to service recipients and the way employees work. In such a process, one of the most important expectations of the organization is that its stakeholders (such as employees, customers, suppliers) adopt and adapt to innovations.

A better understanding of how technological products and services or innovations are accepted by users is important for strategy development and planning. For example, in 2013, Tidd and

Bessant stated that half of all innovations never reach their intended markets (Uncu, 2014). Failed technology investments not only cause financial losses but also lead to dissatisfaction among the organization's employees (Godoe and Johansen, 2012). Therefore, it is of critical importance to adopt innovations and identify the reasons for resistance to change. Different theories and models have been developed for this purpose.

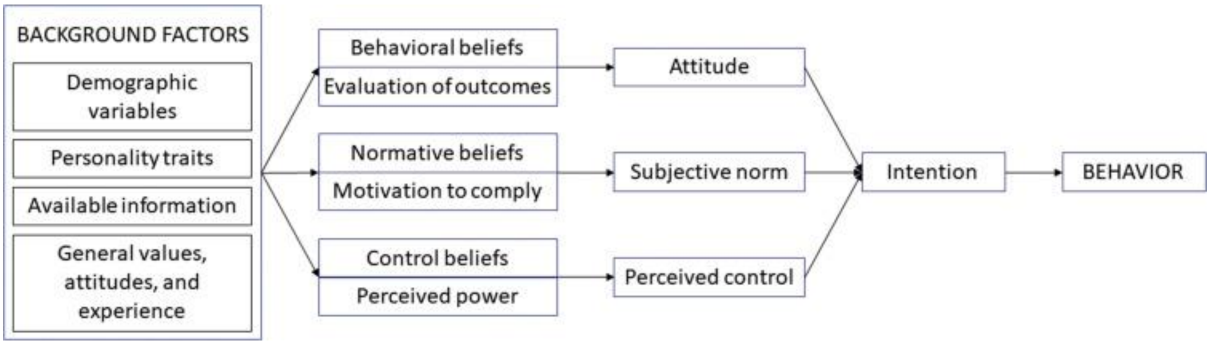
Theory of Reasoned Action

One of the widely studied theories regarding the adoption of new technologies and innovations is the Theory of Reasoned Action, developed by Fishbein and Ajzen in 1975. This theory is used to explain human behavior, starting from the assumption that "people are generally quite rational and systematically use the information presented to them." The theory argues that individuals go through the process of contemplating the potential consequences of their actions before taking action. It states that in order to understand behavior, one must first understand the intention to perform the behavior and the factors underlying that intention (Enér, 2015).

Intention is determined according to two basic variables: The first is attitude towards behavior, which is a personal factor and expresses a person's positive or negative evaluation of any behavior, which is entirely determined by the individual's own assessment of whether the behavior is good or bad, and it reflects the individual's inclination to take action regarding this behavior. The second factor that influences intention is called subjective norm. Subjective norm refers to the social pressure or support a person feels regarding whether or not to exhibit the behavior. Subjective norm implies that social pressure influences people's perceptions of behavior. According to this theory, if an individual evaluates the relevant behavior positively and believes that the people around them support them in exhibiting this behavior, they are inclined to perform this behavior.

In theory, it is stated that it is necessary to investigate why people hold certain attitudes and subjective norms. This is because attitudes and subjective norms are based on beliefs. Thus, attitudes stem from behavioral beliefs, whereas subjective norms stem from normative beliefs. Behavioral beliefs explain that if a person is positive about the behavior, the likelihood of the behavior occurring will increase, and if the person has negative concerns, the opposite situation will occur. Normative beliefs, on the other hand, express the influence that others who support a behavior will have, and if there is disapproval or lack of support, it expresses the opposite influence. All these factors result in a chain that begins with underlying beliefs and manifests in actual behavior. This process is illustrated in Figure 3. (Enér, 2015).

Figure 3. Theory of Reasoned Action.



Source: Enér, R., (2015). Factors Influencing Consumer Acceptance of New Technology.

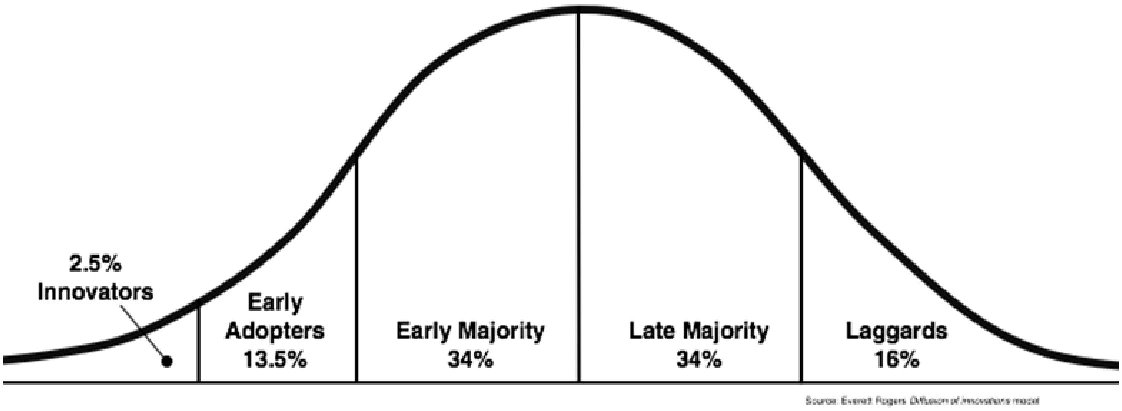
This theory was developed for situations where there is no issue of control regarding behavior. However, many behaviors occur in areas where the individual does not have complete control. Ajzen (1985) expanded the "Theory of Planned Behavior" by introducing the "Perceived Behavioral Control" variable to explain such behaviors where the individual lacks full control and their intention for these behaviors. According to Perceived Behavioral Control, the more resources (time, money, talent, cooperation of people around them) and opportunities an individual has, the greater their control over their behavior (Enér, 2015). When intention is fixed, increasing perceived behavioral control may make it possible to exert the effort required to perform that behavior. For instance, among two individuals with equal intention and effort to ski, the individual with higher self-confidence and belief in skiing is expected to be more successful than the other person.

Adoption and Diffusion Theory

Rogers' Adoption and Diffusion Theory is another widely used theory in information systems research. The Diffusion of Innovation Theory explains the process of acceptance or rejection of innovation by highlighting the perceived characteristics of the innovation. Rogers aimed to determine how the characteristics of innovation affect the adoption rate in his study. Adoption has been described as "deciding to use the innovation in the best possible way" (Enér, 2015).

In his theory published in 1995, Rogers outlined the process of adoption and diffusion of innovation in five stages, as stated in Figure 4: knowledge, persuasion, decision, implementation, and confirmation. In the knowledge stage, individuals acquire information about the functions of the innovation. In the second stage, they evaluate the advantages and disadvantages of the innovation and form their attitude towards it. The third stage, the decision stage, involves individuals accepting or rejecting the innovation based on the information they have gathered. At this stage, most individuals pay more attention to the evaluations of people around them rather than the research of experts, and the evaluations they receive from their social circles are more influential in their decisions. If the decision to accept the innovation is made, the fourth stage, implementation of the innovation, follows, and then the final stage, confirmation and reinforcement of the decision, takes place. A shorter acceptance time by the individual is expected to lead to a faster spread of the innovation.

Figure 4. Adoption and Diffusion Theory.



Source: Landau et al. (2022).

Relative advantage is the degree of evaluation of whether the innovation offers an advantage over the product, service, or process it replaces. As the relative advantage increases, so does the likelihood of adaptation to the innovation. Compatibility refers to the extent to which the innovation aligns with a person's past values, experiences, and needs. The more the innovation fulfills the needs of individuals, the higher the level of adoption. Complexity is inversely related to the speed of innovation adoption. Simpler innovations are more likely to be adopted than complex ones. To adopt complex innovations, individuals must possess a high level of knowledge, skills, and experience. Trialability, according to its feature, allows individuals to test the innovation during the adoption stage before it spreads, increasing the likelihood of adoption and acceptance. Lastly, observability entails that the results of innovation adoption can be observed and communicated by others.

There are four significant obstacles to innovation adoption. The first of these is economic barriers. Expenses pose the initial hurdle to the benefits of innovation. The second are behavioral barriers, such as priorities, motivations, rationality, and inclination toward change or risk. The third is organizational barriers, including goals, routines, power dynamics, influence, culture, and stakeholders. Finally, there are structural barriers such as management, sunk costs, and infrastructure. For these reasons, large and complex systems tend to change only gradually (Uncu, 2014).

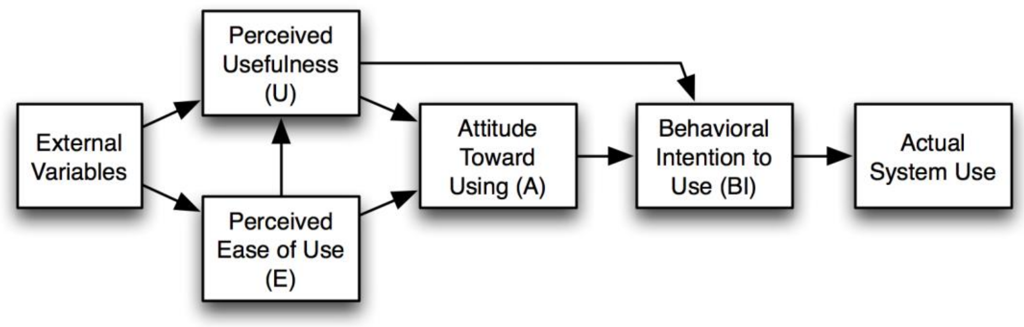
Rogers categorized people into five groups based on their processes of adapting to innovation. These are innovators, early adopters, early majority, late majority, and laggards. Innovators are the first to accept and adapt to innovation. They possess sufficient economic resources and motivation. Innovators are courageous and enterprising individuals who are not afraid to take risks. They can handle ambiguity more easily and have a better understanding of complex information. Innovators play a crucial role in the diffusion process of innovation. They are the ones who initially adopt innovation, introduce it to the environment, and transfer it to others. Although early adopters do not possess all the characteristics of innovators, their influence on other groups is significant. Other groups trust early adopters more and are more influenced by their decisions. If early adopters succeed in adopting an innovation, the likelihood of all other groups adopting it increases. Individuals in the early majority group adopt innovation earlier than those at the average level. Their adoption process takes longer than that of early adopters, and they observe the choices and decisions of early adopters, shaping their own decisions accordingly.

Technology Acceptance Model

In 1986, Fred D. Davis proposed a different model to the Theory of Reasoned Action and called it the Technology Acceptance Model (TAM). This model was developed to explain and predict individuals' acceptance behavior towards technological innovations. Davis restructured the Theory of Reasoned Action from a technological perspective and stated that the social effects (subjective norms) of the Theory of Reasoned Action do not align with the logic of acceptance and adoption of technology (Enér, 2015). When these two theories are compared, while the Theory of Reasoned Action explains various human tendencies, TAM focuses on the technology user's acceptance behavior (Lundberg, 2017).

Acceptance has been defined as an individual's decision to become a regular user of a product (Peeters, 2013). TAM serves two purposes. Firstly, it predicts user acceptance of computer-based information systems. Secondly, it explains what changes should be introduced to the computer-based information system to increase its acceptability by the user (Lundberg, 2017). TAM is based on two fundamental concepts. As depicted in Figure 5, these concepts are stated as perceived usefulness and perceived ease of use, which are utilized to elucidate the adoption of a new technological system. Davis defines perceived usefulness as "an individual's belief that using a particular system will enhance their job performance" (Davis, 1986, p. 26). Perceived ease of use is defined as "an individual's belief that using a particular system does not require physical or mental effort" (Davis, 1986, p. 26). Davis posits that when a system is easier to use, overall business performance will improve. This definition indicates that perceived ease of use directly impacts perceived usefulness. Studies comparing these two concepts have shown that perceived ease of use is the primary determinant of the intention to use new technology. Although both concepts influence the attitude towards use, it has been stated that perceived ease of use has a direct relationship with the intention to use (Enér, 2015).

Figure 5 . Technology Acceptance Model.

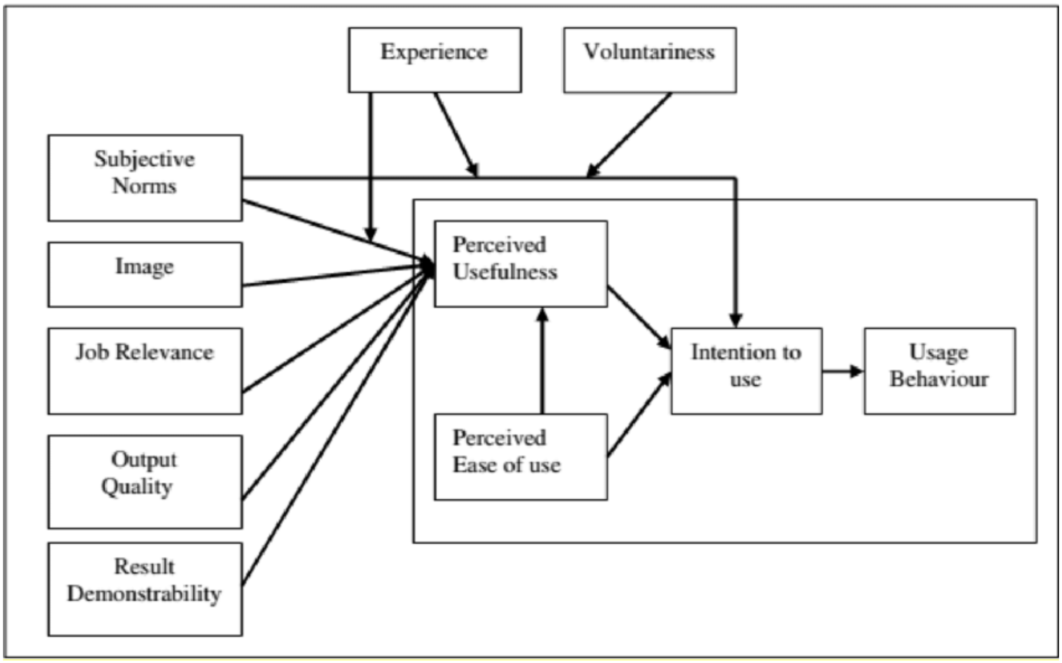


Source: Enér (2015)

TAM emerged to predict the use of information systems in the business environment. However, subsequent studies found TAM's explanations of customer technology acceptance to be insufficient, leading to arguments for its expansion to include different technologies, users, and organizations. Davis also agreed on this issue and acknowledged that further studies should be conducted to determine other variables that affect the usefulness, ease of use, and acceptance of technology. Consequently, new variables and studies on different subjects have been carried out to expand the original TAM. In addition to the findings of TAM, it has been determined that trust is a critical factor in the use of online trading sites, and that the perception of risk in online banking usage is more descriptive than perceived benefit and perceived ease of use. It has also been found that social influence, along with trust and risk perception, plays a significant role in the acceptance and usage behavior in early adopter groups. Social influences have been stated to impact willingness and attitude toward adopting new technologies. Various studies have identified different factors affecting behavioral intention. Consequently, TAM was criticized for not incorporating personal characteristics (Peeters, 2013).

In 2000, Venkatesh and Davis conducted a study that expanded the original TAM and named it Technology Acceptance Model 2 (TAM2). The model was expanded with the addition of social influences and cognitive tools. Social impacts include subjective norms, image, and voluntariness. These effects are illustrated in Figure 6 (Enér, 2015).

Figure 6. Technological Acceptance Model 2.0.



Source: Su & Li (2021).

A subjective norm shows that a person is impacted by those who are significant in their social circle. "The use of innovation on a voluntary basis or with free will" is one definition for voluntariness. Image is the last idea in the context of social impacts. Improving one's standing or image in their social surroundings is the definition of image in the TAM2 model. Venkatesh and Davis identified three cognitive tools: output quality, demonstrability of the outcome, and relevance to the task. The definition of "business relevance" is "an individual's perception of the target system's applicability to their job." It is believed that perceived usefulness is directly impacted by compatibility with the task. This is predicated on the idea that a person is aware of the innovations and systems they require to do a task. The quality of the output is the second cognitive variable. It may be characterized as a person's perception of the capabilities of a system and how well it executes particular tasks. The outcome's demonstrability is the third variable. It is described as "the tangibility of the results of using the innovation" and is closely tied to perceived benefit. People are inclined to see an invention's benefits more strongly if the innovation produces more observable consequences. The experience impact is a moderator variable that was introduced to the research in addition to these other factors (Enér, 2015).

In 2000, Moon and Kim expanded TAM and added perceived playfulness as a motivational factor, stating that perceived playfulness had a stronger effect than perceived usefulness (Peeters, 2013). Perceived playfulness, also described as intrinsic motivation, is the engagement in an activity for pleasure and fun rather than for external rewards (Enér, 2015).

It is defined as believing that one is welcome. It has been determined that visual appeal has a positive effect on the acceptance of using the website. In studies conducted on products, it has been found that mobile phones with high perceived visual appeal have higher usability and perceived overall performance than mobile phones with low perceived visual appeal (Enér, 2015).

Dabholkar and Bagozzi (2002) also stated that personal characteristics such as self-efficacy, novelty-seeking, need for interaction, and self-awareness have moderating effects between perceived ease of use and intention to use technology (Peeters, 2013).

TAM is a model that has been used and supported in many studies. Although the original TAM has been expanded by adding many different variables, the perceived usefulness and perceived ease of use variables still remain current and fit for purpose. One of the biggest criticisms of TAM is that personal characteristics and external stimuli are not accounted for. The Technological Readiness Model, proposed by Parasuraman in 2000, explains adaptation to technology by considering the individual's personal characteristics as an alternative to TAM (Peeters, 2013).

Technological Readiness Index

As people's dependence on technology increases and the way businesses operate evolves, people's readiness for technology and their inclination toward it become crucial in the utilization of technology.

In 2000, a scale known as the Technological Readiness Index was developed by Parasuraman to measure people's readiness for technology. Technological readiness is defined as "people's tendency to use and adopt new technologies in line with their goals in private or business life". In this study, Parasuraman noted that technology can evoke both negative and positive emotions. It has been stated that these feelings vary among individuals and lead to differences in people's propensity to use and adopt new technologies. There’s a popular term for the research in NASA, which is also called Technological Readiness Index, this is not the case in this research, author asks not to confuse these terms.

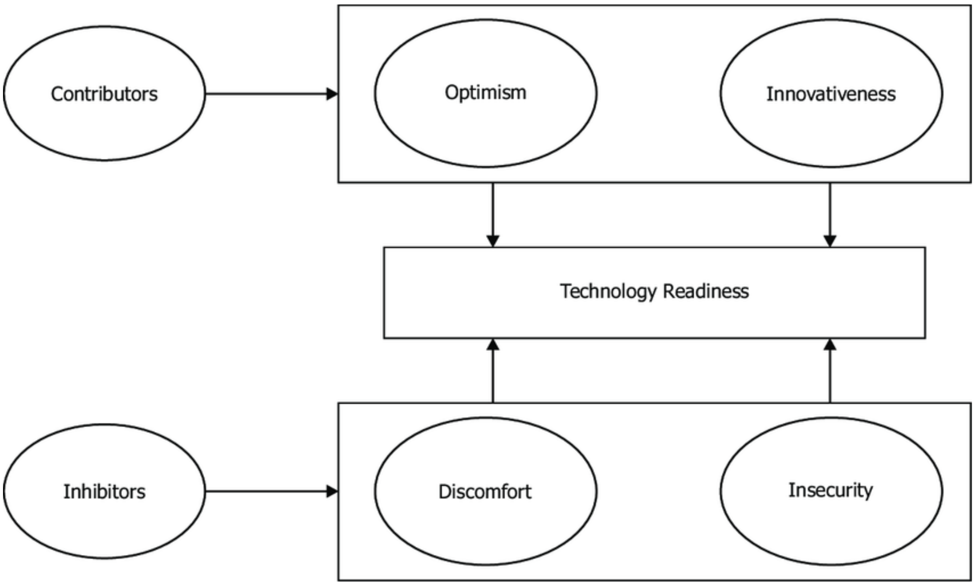
Based on his research, Parasuraman categorized people's attitudes toward technology into four parts:

a) Optimism: Having a positive outlook toward technology and the belief that technology enhances control, flexibility, and effectiveness in people's lives.
b) Innovativeness: Being a technology pioneer and leader.

c) Discomfort: Feeling of being unable to control technology and being overwhelmed by it.
d) Insecurity: Tendency to distrust technology and be skeptical about its proper functioning.

Among these four parts, optimism and innovativeness act as drivers of technological readiness, while discomfort and insecurity act as inhibiting factors. This framework is illustrated in Figure 7.

Figure 7. Technology Readiness Model.



Source: Uncu (2014).

Optimism:

It has been stated that optimists are more likely to embrace technology and focus on its positive aspects compared to other consumers (Lundberg, 2017). Examples of optimists who generally view technology favorably are as follows (Peeters, 2013):

a) People who appreciate using computers because they offer flexibility in adhering to standard working hours.
b) Individuals who believe that technology grants them greater control over their daily activities.
c) People who perceive technology as enhancing the efficiency of people's tasks.

A study on self-service technologies revealed a positive correlation between optimism and the adoption of self-service technologies. Initial research in the fast-food industry showed that orders placed via touch screens empowered customers with a sense of control. This perception of control positively influenced the use of self-service kiosks in restaurants and airports. Subsequent studies highlighted the importance of control and efficiency as criteria for customer acceptance of self-service technologies. Thus, optimism has been suggested to have positive effects on perceived usefulness and perceived ease of use (Lundberg, 2017).

Innovation:

Innovators, defined as technology pioneers and leaders, are bold in their adoption of technology. Due to their elevated level of technological knowledge, innovative consumers perceive technology more readily and exhibit a greater eagerness to learn new technology. Because innovators find technology inherently fascinating, they tend to perceive new technologies as more useful and easier to adopt than others (Lundberg, 2017). Examples of behaviors typical of innovators include (Peeters, 2013):

a) They readily adopt new technologies without assistance from others.
b) They are early adopters of the latest technologies.
c) They utilize new services and products before the majority of people around them.

The positive impact and reliability of innovation in technological readiness studies have been questioned. The main reason for this is stated to be measurement without taking into account the difference between innovation in general and innovation in a specific product or service. Overall, the impact of innovation on the adoption of technologies did not appear to be very high. However, a strong relationship has been identified between innovativeness and technology adaptation toward a specific product or service in a particular field. Interestingly, there are studies showing that innovativeness may have a slightly negative effect on perceived ease of use. As an explanation for this, Walzuch et al. (2007) stated that innovative people are more critical of technology because they are aware of the latest developments. Another suggested explanation comes from Godoe and Johansen (2012), who stated that people with high innovativeness are more willing to accept and use new technologies but explained that it is easier for innovative people to stop using systems due to their high expectations of new technologies.

In response to the criticisms, Parasuraman and Colby rearranged the technological readiness index and re-evaluated the measurement. They stated that innovative people enjoy learning new and complex technologies and therefore tend to adapt to highly innovative technologies. Subsequent reconsiderations suggested that innovativeness has positive effects on perceived usefulness and perceived ease of use.

Discomfort:

Discomfort pertains to the inclination to experience "a lack of control over technology and a feeling of being overwhelmed by it." Individuals who are uncomfortable with technology often exhibit resistance to change and innovation, fear of technology, anxiety toward technology, and generally adopt a negative attitude when faced with using new or unfamiliar technology (Lundberg, 2017). Characteristics of individuals uncomfortable with technology include (Peeters, 2013):

a) They believe that technology is not designed for ordinary people to use.
b) They feel that they do not comprehend explanations when provided about new services or products.
c) They perceive individuals providing information about the product or service as exploiting them due to having more information.

Studies have revealed that discomfort with technology is akin to perceived usefulness and perceived ease of use of technology. A decrease in perceived ease of use appears to exert a significant negative influence on an individual's acceptance of technology. As Meuter suggested, disorders such as technology anxiety may be a contributing factor to an individual's avoidance of technology. Hence, there exists a negative relationship between discomfort and technology acceptance. It has been proposed that discomfort has a detrimental effect on perceived usefulness and perceived ease of use (Lundberg, 2017).

Distrust:

Distrust has been defined as the inclination to doubt technology and harbor skepticism regarding its proper functioning. Individuals who distrust technology believe that it seldom operates correctly and is prone to breakdowns or errors at critical moments. Consequently, individuals with a disposition of distrust towards technology are regarded as having low technology adoption rates. They perceive technology as less useful and challenging to use. It has been emphasized that individuals who distrust technology tend to resort to using it compulsively only when no alternative option is available, rather than embracing it willingly (Lundberg, 2017). Characteristics of individuals who distrust technology include (Peeters, 2013):

a) They are averse to engaging with businesses that solely offer online services.
b) They lack confidence in the success of transactions conducted over the internet or via machines.

Similar to innovativeness, various interpretations have been posited regarding the impacts of insecurity on technological readiness. For instance, in cases of distrust, perceived benefit is not necessarily negative; instead, it has been argued that individuals expect to discern the fundamental value of the system irrespective of overcoming the technological hurdles. In line with this, studies have been conducted indicating that the effects of insecurity are minimal. However, rather than asserting that distrust is entirely inconsequential, it is suggested that distrust indeed exerts a negative impact and should be assessed alongside a potent effect such as discomfort.

Despite critical studies, Parasuraman and Colby found in their 2015 study that distrust has a strong correlation with a lack of trust in technology, leading to a diminished inclination to use technology. Consequently, it has been suggested that distrust exerts a negative influence on perceived usefulness and perceived ease of use (Lundberg, 2017).

Technological Readiness Segmentation:

Segmentation studies were also conducted based on the Technological Readiness Index. In 2001, Parasuraman and Colby devised a segmentation scheme based on the four components of the index, resulting in five segments: Explorers, Pioneers, Skeptics, Hesitators, and Avoiders.

Researchers, as the first group to embrace technology, are individuals who readily show interest when presented with a new technological product or service (Tsikriktsis, 2004). They exhibit high motivation and low resistance to technology (Parasuraman and Colby, 2015).

Pioneers are the segment that follows researchers in adopting technology. They hold both positive and negative views about technology (García and Payán, 2016). They are eager to reap the benefits of technology but also contemplate its challenges and risks (Tsikriktsis, 2004), exhibiting some resistance (Rose and Fogarty, 2010).

For example, as depicted in Table 2, researchers and pioneers score high in the innovation and optimism sections. Doubters and avoiders score high on other components of the index, namely discomfort and distrust. Skeptics have faith in technology and are optimistic, yet they are not inclined toward innovation (Rose and Fogarty, 2010). They harbor concerns about the risks of technology and experience feelings of insecurity and discomfort. They adapt to technology when the proliferation of technology users begins to plateau (Rose and Fogarty, 2010).

Avoiders are the segment that refrains from adopting technology unless absolutely necessary (Tsikriktsis, 2004). They exhibit the highest resistance to technology and the lowest motivation (Parasuraman and Colby, 2015).

Skeptics, on the other hand, represent the segment in the middle of the five segments, requiring persuasion regarding the benefits of new technologies (Tsikriktsis, 2004) and holding neither extremely positive nor extremely negative views. Skeptics are not opposed to technology, but they show minimal interest in it and await proof of its benefits before embracing it (Rose and Fogarty, 2010).

Table 2. Technological Readiness Segmentation.

Technological Segmentation	**Optimism**	**Innovation**	**Discomfort**	**Distrust**
Researchers	High	High	Low	Low
Pioneers	High	High	High	High
Hesitators	Low	Low	Low	Low
Sceptics	High	Low	High	High
Avoiders	Low	Low	High	High

Source: Parasuraman & Colby (2015).

The technological readiness index is applied to both customers and employees, aiding in segmenting customers based on their predispositions due to demographic differences and determining which technologies to offer accordingly. Understanding the technological readiness of employees facilitates informed decisions regarding the establishment of employee-technology engagement. It offers insights on assessing employees' inclination toward technology, placing them in suitable roles, and providing necessary training.

2.3 Organizational Readiness for Change on the Use of Artificial Intelligence

The concept of change, which involves bringing something from one level to another, can be encountered at personal and institutional levels. The most important features of change at the personal level are; the constant development of new ways of doing business by individuals, the mental adjustment to constantly behave differently, and their resistance to change. Organizational change refers to the change in the structure, composition, and behavior of the organization. Institutional change is defined as an inevitable process that can be positive or negative, beneficial or harmful, short-term or permanent, rapid or gradual, planned or unexpected, and involves the transition of a system or process from one state to another. Since corporate change management generally requires multiple changes such as workflow, decision-making, communication, and reward systems, it necessitates simultaneous arrangements with employees (Errida and Lotfi, 2021).

According to Lewin's change model, which is widely used regarding the change model and process, change in organizations consists of a three-stage process: thawing, change, and refreezing (Hussain et al., 2018).

1. The thawing phase includes the process of convincing people who may have a rigid and negative attitude towards change about the necessity of change.
2. The second stage is the actual implementation of the change.
3. In the third stage, the aim is for the innovations made in the change phase to become the routine of the institution and to be institutionalized.

For this reason, regarding any issue that is desired to be changed, the internal and external reasons that force change should be determined, and then possible sources of resistance that will try to prevent the change should be estimated (Hussain et al., 2018).

The reason why the system fails is that employees resist change and the institution does not prepare for the innovation intended to be changed. Although change is inevitable at both individual and institutional levels, it is a known fact that people resist change, more or less, openly or implicitly, immediately or over time. Employees may resist any changes to be made in the institution. Therefore, for an application to be carried out successfully, employees must be ready for change and willing to accept the change (Weiner et al., 2008).

It is a challenging process to adapt system changes related to information and communication technologies, which have become widely used in all areas of public institutions of developed countries (Mahendrati & Margundjaya, 2020). However, many public institutions face failure despite spending large amounts. A study by Kaplan (2000) reported that the failure rate of information technologies/systems innovations in healthcare institutions may be high.

The primary reason for failure is the failure to evaluate the broader organizational risks associated with information technology/systems innovation. With risk assessment:

- Hazards related to information and communication technologies innovation are identified,
- The degree of risk associated with each hazard is analyzed, and

- Hazards are prioritized for risk control interventions (Mendes, Marques, & Soares, 2024).

An important way to identify information technology/systems innovation hazards is to assess healthcare organizations' readiness for these innovations. During this evaluation, decision-makers can gain information about the features of new information technologies/systems, form an attitude on this issue, and make a decision about the harmony between innovation and the healthcare institution (Mendes, Marques, & Soares, 2024).

Readiness for institutional change is considered a critical precursor to the successful implementation of changes in complex structures such as public institutions (Weiner, 2009). Employees in public institutions exposed to change face at least three types of risks: (Cunningham et al., 2002).

1. Since corporate restructuring poses a threat of job change or job loss, it is thought that perceptions of insecurity negatively affect their readiness for change and limit employees' participation in change activities (Cunningham et al., 2002).
2. The logistical burden of restructuring represents a risk that may reduce readiness for organizational change (Cunningham et al., 2002).
3. Institutional change represents a source of stress that can be significant. Emotional exhaustion and depression for organizational change will reduce readiness and participation in reconstruction activities. Employees who have confidence in their ability to cope with change will contribute to organizational change and be able to resist uncertainties (Cunningham et al., 2002).

Therefore, in order to meet the requirements of change, healthcare institutions must be flexible, adaptable, and constantly renewing themselves; to increase the readiness of employees, it is necessary to emphasize the difference between current and desired performance levels, prevent dissatisfaction, create an attractive vision for a future situation, and increase trust (Weiner, 2009).

When the conditions related to innovation readiness are examined, it is seen that the external environment, personnel, resources, and institutional characteristics come to the fore (Egan et al., 1981).

The concept of readiness for corporate innovation is defined as the level of compatibility between new information and communication technologies and the organization. It is argued that a higher level of preparedness leads to a lower risk of innovation and a more successful ICT innovation outcome. Additionally, lack of information about public institution readiness for new information and communication technologies increases uncertainty for decision-makers and reduces the ability to make effective decisions that will reduce information and communication technologies innovation risks (Kim & Kim, 2020).

Organizational readiness for change is a multilevel construct. Preparation may be more or less at the individual, group, unit, department, or institutional level. It is a construct that, depending on the degree of analysis, has a varied definition, measurement, and interaction with other variables. Organizational members' efficacy and commitment to change in enacting institutional change are specifically referred to as organizational preparedness. Commitment based on “want” motives reflects the highest level of commitment to implementing organizational change. Change effectiveness increases when people share a sense of confidence that they can collectively implement complex organizational change. The more organizational employees value change, the more willing they are to implement change (Weiner, 2009).

The key to using integrated different technologies in today's complex public organizations is to understand the functioning of these complex systems and create a simultaneous adaptation platform for everyone working together. Change will be possible faster and more harmoniously in an organizational structure where everyone participates in the process, communication is transparent, information is clear, everyone can follow the stages of change, and is informed about the processes (Elliot, 2020).

Information technologies, documentation procedures, etc., used by public institutions to increase their efficiency, process-based innovations have advantages for organizations such as ensuring cost efficiency, increasing the quality of services, increasing safety, increasing satisfaction, effectiveness, and efficiency (Cawsey et al., 2012;; Pasiopoulos et al., 2013; Piening, 2011; Simpson & Dansereau, 2007). When the values formed within the organization as a result of innovation practices are compatible with the values shared within the existing structure of the organization, the practices are adopted more easily (Klein & Sorra, 1996).

In today's world where information and communication technologies are extensively used, compliance with technology or acceptance of information technology by users/employees is very important. User resistance is a significant obstacle to the implementation of information systems. If a system does not meet users' needs or if users do not believe in the system's benefits, they may resist or reject new technology. In a public institution where user resistance is encountered, the advantages provided by information technologies may, after a while, turn into loss of time and effort, decrease in productivity and service quality, increase in cost, and idle technology (Desmet, 2014). For this reason, knowing the readiness levels of users for information systems allows determining their needs in this regard and making a plan, program, and preparation appropriate to these needs. Thus, improving technology acceptance and more effective use of technology can be achieved by taking steps towards this goal.

According to Bouckenooghe (2010), readiness encompasses people's attitudes, beliefs, and intentions on the degree of change that has to be implemented as well as the ability of organizations to carry it out effectively. The ability of people to embrace and use new technologies to accomplish their goals is referred to as technology readiness. It is a conglomeration of both favorable and unfavorable views toward technology. It is thought that people hold different beliefs. An individual's inclination to use new technology is determined by their coexisting beliefs taken together (Parasuraman & Colby, 2001).

Readiness for change on the use of Artificial Intelligence refers to the preparedness of public institutions for the expected change brought about by Artificial Intelligence Technologies (Madan & Ashok, 2023). Individuals' readiness for change on the use of Artificial Intelligence begins with the perception of the benefits of change, the risks of not being able to change, or the demands of externally imposed changes (Hradecky et al., 2022).

Assessment of readiness is a critical process to determine the risks of innovation applications related to AI to be used in the provision of public services (Madan & Ashok, 2023). The assessment of readiness on the use of AI includes the adaptation of the AI to the existing system within the organization, the concerns of employees regarding the change, evaluating how the workflow will be affected by the change brought by the AI practices, balanced support of innovation within the organization as a whole, and special preparation for AI (Selten & Klievink, 2024).

Existing features of public institutions contribute to structural or non-structural readiness to support AI-related innovations. Structural features such as the hardware and telecommunication capabilities of the institution reflect the physical design of the punlic institution and support routine information management operations. Non-structural characteristics, such as employees' attitudes towards AI, reflect the public institution's informal work environment, culture, and values regarding information management (Guedes & Oliveira, 2024).

Readiness for the use of AI as in any other new technology case consists of different dimensions. These are:

1. Information sub-dimension: General and specific information required for managers when deciding on AI innovations (Snyder-Halpern, 2001).

2. User skills sub-dimension: It refers to the characteristics of individuals involved in the process of AI usage. These features include the user's technology background, skill level, previous experience with technology innovation, information and communication technologies. It includes support for implementation processes, degree of satisfaction with existing information and communication technologies, level of commitment to the institution, and reaction to change (Snyder-Halpern, 2001).
3. Technical sub-dimension: It is the ability of public institutions' existing hardware and software to support AI innovations. The evaluation is based on the harmony between existing technical architectures and innovation features of information and communication technologies (Snyder-Halpern, 2001).
4. Operation sub-dimension: It is the harmony between the innovation features of information and communication technologies and the operational features of existing information and communication technologies. It includes issues such as accessibility, ease of use, processing speed, reliability, durability, and consistency with clinical/administrative application processes (Snyder-Halpern, 2001).
5. Process sub-dimension: It is the harmony between information and communication technologies innovation features and existing administrative application processes. A high level of process readiness indicates that new information and communication technologies have features that closely match existing application processes (Snyder-Halpern, 2001).
6. Resources sub-dimension: It assesses the ability of the public institution's information and communication technologies to support AI innovations. This sub-dimension covers a wide range of assets such as technical documentation, availability of on-site trainers, 24-hour emergency support, and user advisory services (Snyder-Halpern, 2001).
7. Values and goals sub-dimension: It examines the alignment between the existing structural and non-structural features of the public institution and the innovation features of information and communication technologies (Snyder-Halpern, 2001).

The system development life cycle consists of three sub-dimensions (Snyder-Halpern, 2001):

1. During the planning and analysis process, decision-makers define the public information management problem and analyze the impact of the problem on practice processes and activities. This helps in determining the most appropriate information and communication technologies solution (Snyder-Halpern, 2001).

2. During the design process, the requirements identified during the planning and analysis process are utilized to build, purchase, or customize information and communication technology innovations. This process is developed in a user-oriented and process-controlled manner. It includes the processes of evaluating and comparing personal system modules, integrating the combination of personal modules into the overall system, and testing the overall system (Snyder-Halpern, 2001).
3. During the implementation and evaluation process, information and communication technologies innovations are evaluated through field audits as they are accepted by users and their use becomes widespread within the institution. System acceptance occurs when users begin to use information and communication technology innovations based on their perceptions of usefulness and ease of use. Acceptance of successful ICT innovations occurs when users start to routinely use them. As users accept and start to apply information and communication technologies innovations, their interaction with each other increases, leading to the widespread use of these innovations (Snyder-Halpern, 2001).

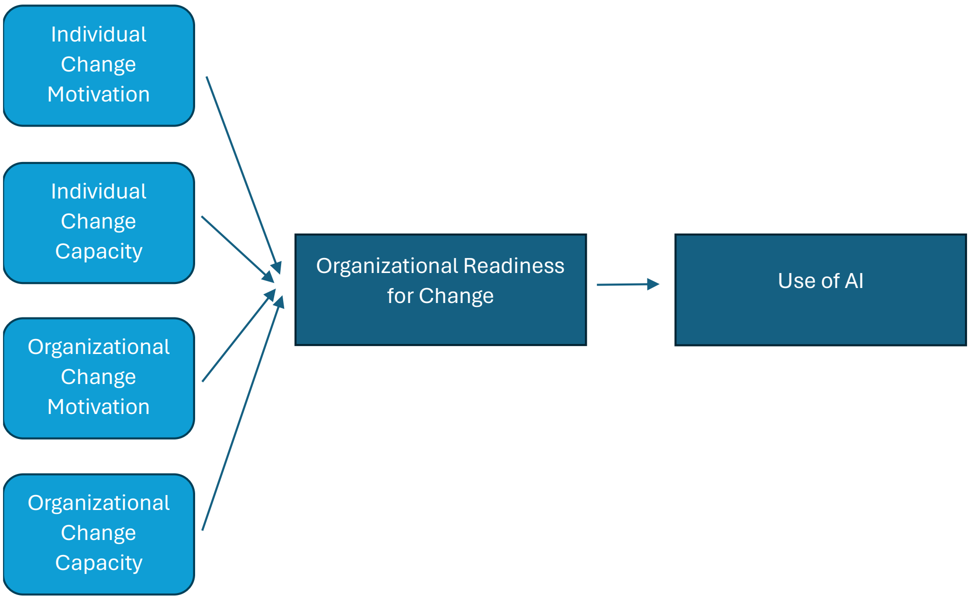
The readiness of every public institution for information and communication technology innovations is specific to that institution, and these different readiness levels also indicate that the readiness of public institutions is not uniform (Snyder-Halpern, 2001).

3. Methodology

3.1 Conceptual Model

This study, which examines the relationship between organizational readiness for change and use of AI, is quantitative research. As seen in Figure 8, the existence and level of the effect of the two variables in question, i.e. readiness for change and it is effect on the use of AI, and whether the two variables change according to demographic variables will be investigated.

Figure 8. Conceptual Model.



Source: own construction.

Hypotheses:

H1: Organizational readiness for change has a significant positive impact on use of AI in the Public Sector Organization of Azerbaijan.

H1$_a$: Individual change motivation has a significant positive impact on use of AI in the Public Sector Organization of Azerbaijan.

H1$_b$: Individual change capacity has a significant positive impact on the use of AI in the Public Sector Organization of Azerbaijan.

H1$_c$: Organizational change motivation has a significant positive impact on the use of AI in the Public Sector Organization of Azerbaijan.

H1$_d$: Organizational change capacity has a significant positive impact on the use of AI in the Public Sector Organization of Azerbaijan.

H2: Organization readiness for change differ according to demographic variables.

H3: Use of AI differ according to demographic variables.

3.2 Data Supply and Sampling

In the research world, survey is a major part of quantitative analysis. This method involves gathering data that can be measured and computed, with the aim to find statistical results for drawing conclusions or making choices. The survey I did shows primary data collection because we got information straight from those participating – they gave us their own accounts or answers when we asked them questions.

Surveys as a method for primary data collection have some benefits. They make it possible to gather particular data that fits with the research question or hypothesis. This type of primary information can be more relevant and timely when compared to secondary sources which might not match current context, they could also have age problems or may not be totally useful for the study's scope Furthermore, having control over the process of data collection allows the researcher to guarantee accuracy and excellence in the collected data.

The participants in the study are the staff members of the Azerbaijani Ministry of Education. The study used a convenience sampling approach, which offers benefits in terms of time and cost savings by including all respondents to the questionnaire in the sample until the target sample size is reached (Graves, Hamada, Booker, Decroix, & Chilcoat, 2007). A non-probability sampling technique called convenience sampling chooses the population for the survey based on who is easiest for the researcher to reach. Since convenience sampling is most often utilized for student research, it is most appropriate given the options and skills available to a single student (ScienceDirect, 2017).

The necessary sample size is computed according to the following formula:

$$\textit{Necessary Sample Size} = [(\textit{Z score})^2 \times \textit{standard deviation} \times (1 - \textit{standard deviation})] / (\textit{margin of error})^2 = 72 \textit{ respondents}$$

Source: https://www.calculator.net/sample-size-calculator.html?type=1&cl=95&ci=5&pp=5&ps=2700&x=93&y=14

, where confidence level = 95%

Margin of error = 5%

Population proportion = 5% (number of Ministry of Education workers over the number of Public Sector Organization employees in Azerbaijan).

Population Size = 2700 (number of employees in the Ministry of Education of Azerbaijan).

3.3 Data Collection Tools

A questionnaire consisting of an information form including demographic characteristics of the participants, a performance scale and a motivation scale is used to collect the data.

The organizational readiness for change scale, which is adapted from the study of Y. Jo and A. Hong (2023), is used to assess the performance of the employees. The scale consists of 28 questions, the first 6 questions are used to measure individual motivation to change, the next 6 questions are designated to measure individual change capacity, the following 6 questions are for organizational change capacity, and the remaining 10 questions are for organizational change capacity (See Appendix). The questionnaire consists of 5-point Likert type questions (1: Strongly Disagree, 5: Strongly Agree).

The use of AI scale of this study was adopted from the study of J. Chen (2019). The scale consists of 4 questions (1: Strongly Disagree, 2: Disagree, 3: Undecided, 4: Agree, 4: Agree, 5: Strongly Agree) in a 5-point Likert-type scale that examines the adoption of AI. The low scores indicate a low level of AI use, while high scores indicate a high level of AI use.

3.4 Data Collection and Ethical Issues

In line with the study's objectives, datawas gathered from Ministry of Education staff members by means of questionnaires from September 1, 2024, to March 15, 2024. The researcher at the Ministry distributes the surveys via social media, email, or personal delivery. Data gathering involved volunteer participation. Participants received information prior to the survey on the aim of the research, instructions for completing the forms, and the confidentiality of their replies and personal data.

3.5 Statistical Method

First, the sub-dimensions of the organizational readiness scales and the items that relate to these dimensions are identified. Exploratory and Confirmatory Factor Analyses are then applied to both organizational readiness and the usage of AI measures. For additional analysis, the scale scores with sufficient levels of validity and reliability are retained. The arithmetic averages of the responses provided to the pertinent items are used to determine the participants' scale scores. The kurtosis and skewness metrics are used to examine the scores' normal distribution. According to Camparo (2013), the kurtosis and skewness values within the range of -2 to +2 are recognized as the standard for adherence to the normal distribution. Simple linear regression analyses are performed to test the significance of relationships. Stata statistical software is employed to carry out all the necessary tests.

3.6 Reliability Analysis

The Cronbach's alpha coefficient obtained within the scope of the reliability analysis shows the reliability level of the scale. The value of the coefficient varies between 0 and 1, and if the coefficient value is greater than 0.700, it can be stated that the scale is reliable. Considering the calculated Alpha (α) coefficient, the reliability level of the scale can be interpreted as follows (Peterson, 1994):

I. It is not reliable if $.00 \leq \alpha < .40$

II. It is weakly reliable if $.40 \leq \alpha < .60$

III. It is quite reliable if $.60 \leq \alpha < .80$

IV. It is highly reliable if $.80 \leq \alpha < 1.00$.

3.7 Validity Analysis

Exploratory factor analysis is used to reveal the construct validity of a scale in a statistical sense. First, KMO and Bartlett tests are performed to determine the scale's suitability for factor analysis. The KMO coefficient is calculated to test the size of the sample. Within the scope of factor analysis, the distribution in the population is expected to be normal distribution. This situation is also examined with the Bartlett test. In this context, it is necessary to obtain a value of .50 and above as a result of the KMO test measurement, and to be statistically significant as a result of the Bartlett sphericity test (Jung & Lee, 2011). In this context, the result of the KMO test should be close to 1,000, and the result of the Bartlett sphericity test should be statistically significant. The Scree Plot graph showing the scattering of the eigenvalues of the factors and the explained variance ratio are used to determine the total number of factors related to the scale. In factor analysis, factor load values should be taken as a basis while matching the items of the scale to the factors or removing them from the scale content. A coefficient that predicts how the factors and items will relate to one another is called the factor loading value. A high load value in the factor that the items belong to is the intended outcome. A factor load of less than 0.30 for each item, or a difference of less than 0.10 between the factor loads of the item in question in two distinct factors, indicates that the item is eliminated from the scale, and further analysis can proceed.

4. Analysis and Findings

Within the scope of our research, primarily the demographic data of the participants were analyzed and the results are shown below.

4.1 Demographic Statistics

The following are the demographic statistics of the participants of the survey.

Table 3. Demographic Statistics.

Variable	**Share**	**Number of Respondents**
	Gender	
Male	59.7%	43
Female	40.3%	29
	Age	
18-24	23.6%	17
25-34	54.2%	39
35-44	15.3%	11

45-54	4.2%	3
55 and more	2.8%	2
	Marital Status	
Currently Single	52.8%	38
Currently Married	47.2%	36
	Education	
High School or Some College	0	0
Bachelor's Degree	41.7%	30
Master's Degree	56.9%	41
Doctoral Degree	1.4%	1

59.7% (n=43) of the sample are female respondents, whereas 40.3% (n=29) are male respondents.

The respondents in the age range of 25-34 is the majority of the sample size with 54.2% (n=39) of share, which is followed by the second largest group of respondents in the range of 18-24 with 23.6% (n=17) of share. The respondents in the age range of 35-44 comprised 15.3% (n=11), 45-54 comprised 4.2% (n=3), and 55 and more comprised 2.8% (n=2) of the sample size, respectively.

The distribution is more equal as compared to other above analyzed variables so as the respondents who are currently single make up 52.8% (n=38) of the sample, whereas the respondents who are currently married make up 47.2% (n=36) of the survey population.

The population of the survey is well-educated individuals on average. 56.9% (n=41) of the respondents stated that their highest educational attainment is Master's degree, 41.7% (n=30) stated that the their highest educational attainment is Bachelor's degree, and only 1.4% (n=1) of the sample size indicated that his/her highest educational attainment is Doctoral degree. No individual having high school or some college being his/her highest educational attainment participated in the survey.

4.2 Results of Reliability Analysis

The output of the employed reliability test is presented in Table 4. Below. As a result, Cronbach Alpha values for all the scale/factors were appeared to be higher than .70, which value considered to be the acceptable (Peterson, 1994). It can be concluded that all the scales/factors are "reliable".

Table 4. Results of Cronbach Alpha Test.

Scale / Factor	*N of Items*	*Cronbach Alpha score*
Organizational Readiness for Change	28	0.848

-Individual Change Motivations	6	0.846
-Individual Change Capacity	6	0.796
-Organizational Change Motivation	6	0.906
-Organizational Change Motivation	10	0.843
Use of AI	4	0.876

Source: Stata output, own construction.

4.3 Validity Analysis

Table 5. Results of the Factor Analysis.

Factor / Statement	*Factor Load*	*Eigenvalue*	*Explained Variance (%)*
1. Factor (Individual Change Motivation)			
Q1	0.809		
Q2	0.748		
Q3	0.727	3.412	15.962
Q4	0.843		
Q5	0.815		
Q6	0.853		
2. Factor (Individual Change Capacity)			
Q7	0.753		
Q8	0.710		
Q9	0.703	7.014	17.679
Q10	0.753		
Q11	0.737		
Q12	0.858		
3. Factor (Organizational Change Motivation)			
Q13	0.808		
Q14	0.688		
Q15	0.714		
Q16	0.683	6.554	17.506
Q17	0.640		
Q18	0.889		
4. Factor (Organizational Change Capacity)			
Q19	0.807		
Q20	*0.831*		
Q21	*0.649*		
Q22	*0.901*		
Q23	*0.707*		
Q24	*0.668*		
Q25	*0.923*	9.871	25.334
Q26	*0.732*		
Q27	*0.912*		
Q28	*0.861*		
Use of AI			
Q29	*0.901*		

Q30	*0.858*		
Q31	*0.844*		
		5.213	23.718
Q32	*0.852*		

Source: Stata output, own construction.

The KMO value in the factor analysis of the organizational readiness for change scale was.797. A valid sample size is indicated by a KMO value greater than.50. Furthermore, the Barlett Test produced a significant result (X-squared=344.083; p<.05). It is therefore possible to conclude that there is enough correlation between the statements on the scale. The KMO value and Barlett test result indicated that the scale data were suitable for factor analysis. None of the statements were excluded from the analysis because all of the factor loads were greater than the allowed rate of.50. Additionally, it was discovered that the factor eigenvalues are greater than 1.00. The factor analysis reveals that the overall variance rate components satisfies the requirement of being greater than 50% (Hair et al., 2014).

As for the use of AI Scale, the KMO value equaled .816, which is above the threshold of .50 indicating that the sampling is valid. As a result of the Bartlett Test (X-squared=766.124; p<.05), it can be concluded that the result is significant and the statements on the scale have a sufficient correlation between each other. According to the KMO and Barlett Test results, it can be concluded that the items in the scale are valid and can be proceeded with further regression analysis. Since all the of the factor loads appeared to be higher than .50, none of the statements were dropped. Thus, the scale can be considered valid.

4.4 Descriptive Statistics

The result of the descriptive statistics for the scales are given below in Table 6.

Table 6. Descriptive Statistics.

Variables	*N*	*Mean*	*Std. Dev.*	*Median*	*Skewness*	*Kurtosis*
Organizational Readiness for change	72	4.208	0.453	4.500	-0.705	2.873
-Individual Change Motivation	72	4.333	0.560	4.375	-0.203	1.768
-Individual Change Motivation	72	4.431	0.511	4.625	-1.073	3.697
-Organizational Change Motivation	72	4.329	0.566	4.429	-0.573	2.470
-Organizational Change Capacity	72	3.738	0.711	3.750	-0.360	2.839
Use of AI	72	3.956	0.604	3.947	-0.312	2.683

Source: Stata output, own construction.

The research participants' average organizational readiness for change score is 4.208, their average individual change readiness score is 4.333, their average individual change capacity score is 4.431, their average organizational change motivation score is 4.329, their average organizational change capacity score is 3.738, and their average use of artificial intelligence score is 3.956.

Skewness and kurtosis values were investigated to ascertain the normal distribution of the scale scores. Divergent views exist in the literature regarding the appropriate skewness and kurtosis values for Likert-scale data that correspond to a normal distribution. According to George and Mallary (2014), the ideal range for skewness and kurtosis values is ±2. Every skewness and kurtosis value in the table falls within the specified range. As a result, it was determined that the study's variables were all distributed normally.

4.4 Difference Tests

Table 7. Independent Sample T-test of Organizational Readiness for Change according to Gender, Marital Status, Education, and Age.

Gender	*N*	*Mean*	*Std. Deviation*	*df*	*t*	*p-value*
Male	29	4.426	0.081	70	-2.007	0.049**
Female	43	4.212	0.068			
Marital Status	N	Mean	Std. Deviation	df	t	p-value
Currently single	38	4.205	0.075	70	-1.882	0.064*
Currently married	34	4.402	0.073			
Educational Status	N	Mean	Std. Deviation	df	t	p-value
Bachelor's Degree	30	4.133	0.436	69	-2.762	0.007***
Master's Degree	41	4.422	0.435			
Age	N	Mean	Std. Deviation	df	t	p-value
Between 18-24	17	4.177	0.099	54	0.352	0.726
Between 25-30	39	4.129	0.080			

Source: Stata output, own construction.

Note: "" indicate significance at 90% confidence level, "**" at 95% confidence level, and "***" at 99% confidence level, respectively.*

The purpose of the study was to ascertain whether the organizational preparedness for change of the participants varied according on age, gender, marital status, or level of education. The independent sample t-test indicates that participants' organizational readiness for change is not affected by age or marital status. When it came to organizational readiness for change, the views of female employees (Avg. 4.212;.068) were less positive than those of male employees (Avg. 4.426;.081), and at the 95% confidence level, the difference seemed to be significant. These results mean that male employees have higher perception of their organizational readiness for change than female employees. Another significant difference was observed according to educational status of the employees. Individuals with the highest educational attainment of a Bachelor's degree demonstrated an average organizational readiness for change of 4.133, whereas those holding the highest educational attainment of a Master's degree demonstrated an average work performance of 4.422. With a p-value of 0.007, we are able to reject the null hypothesis, which states that there is no difference between the two means. Instead, we find that there is a substantial difference in the respondents' educational attainment and organizational preparedness for change.

Table 8. Independent Sample T-test of Use of AI according to Gender, Marital Status, Education, and Age.

Gender	*N*	*Mean*	*Std. Deviation*	*df*	*t*	*p-value*
Male	29	4.105	0.103	70	-1.744	0.086*
Female	43	3.856	0.095			
Marital Status	N	Mean	Std. Deviation	df	t	p-value
Currently single	38	3.924	0.088	70	-0.477	0.635
Currently married	34	3.992	0.115			
Educational Status	N	Mean	Std. Deviation	df	t	p-value
Bachelor's Degree	30	3.965	0.107	69	0.137	0.892
Master's Degree	41	3.944	0.098			
Age	N	Mean	Std. Deviation	df	t	p-value
Between 18-24	17	3.981	0.141	54	0.298	0.767
Between 25-30	39	3.926	0.107			

Source: Stata output, own construction.

Note: "" indicate significance at 90% confidence level, "**" at 95% confidence level, and "***" at 99% confidence level, respectively.*

Finding out if the study participants' Use of AI varied based on their age, gender, marital status, or level of education was one of the goals of the investigation. All participants adopted and used AI in the same way, regardless of any demographic variable, according to the independent sample t-test.

4.5 Correlation Analysis

Pearson Correlation Analysis results for the correlation between organizational readiness for change and use of AI are presented in Table 9.

Table 9. Pearson Correlation Test Results.

Variable	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Organizational Readiness for Change (1)	1	0.673*** (0.000)	0.732*** (0.000)	0.928*** (0.000)	0.799*** (0.000)	0.535*** (0.000)
Use of AI (2)		1	0.291** (0.013)	0.735*** (0.000)	0822*** (0.000)	0.964*** (0.000)
Individual Change Motivation (3)			1	0.425*** (0.000)	0.553*** (0.000)	0.135 (0.258)
Individual Change Capacity (4)				1	0.759*** (0.000)	0.637*** (0.000)
Organizational Change Motivation (5)					1	0.642*** (0.000)
Organizational Change Capacity (6)						1

Source: Stata output, own construction.

Note: "" indicate significance at 90% confidence level, "**" at 95% confidence level, and "***" at 99% confidence level, respectively.*

The study found a positive correlation between Organizational Readiness for Change and all other variables, showing that higher readiness for change in organizations leads to increased utilization of AI, stronger individual change motivation and capacity, as well as greater organizational change motivation and capacity. The correlations are statistically significant with p-values below 0.05, showing strong relationships. The relationship between Use of AI and Organizational Readiness for Change is especially interesting. It has a coefficient of 0.673*** ($p < 0.001$), suggesting that organizations using AI technologies are generally more prepared for change.

4.6 Regression Analysis

In this section of the study, simple linear regression analysis was used to test the hypotheses generated within the parameters of the investigation. Prior to performing the regression analysis, it was verified that there was a linear relationship between the variables and that the dependent and independent variables had a normal distribution. The normal distribution of both dependent and independent variables is indicated in the descriptive statistics for study scales. Following the fulfillment of the assumptions, basic linear regression analysis was used.

Regression Analysis Testing the Relationship between Use of AI and Individual Change Motivation

The findings of bivariate linear regression analysis on whether individual change motivation sub-dimension of organizational readiness for change predicts use of AI are presented in Table 10.

Table 10. Regression Analysis Result for Relationship between Use of AI and Individual Change Motivation.

Dependent Variable: Use of AI	*β*	*t*	*p*
Constant	1.631	6.500	**0.000*** **
Individual Change Motivation	0.639	11.120	**0.000*** **
F	123.670		
Adjusted R^2	0.633		
p-value	**0.000*** **		

Source: Stata output, own construction.

The model is significant overall (p.=0.000), according to Table 10’s F value. As a measure of how much of the independent variable (individual change motivation) in the model can account for the dependent variable (usage of AI), the modified R-squared value is 0.633. It is therefore possible to attribute individual change motivation to 63.3% of the employees' adoption and use of AI. It has been established that individual change motivation significantly improves the use of AI based on the magnitude and sign of the beta coefficient. This finding provides evidence in favor of the H1a hypothesis.

Regression Analysis Testing the Relationship between Use of AI and Individual Change Capacity

The findings of the bivariate linear regression analysis on whether individual change capacity sub-dimension of organizational readiness for change predicts use of AI is presented in Table 11.

Table 11. Regression Analysis Result for Relationship between Use of AI and Individual Change Capacity.

Dependent Variable: Use of AI	*β*	*t*	*p*
Constant	3.124	5.300	**0.000*** **
Individual Change Capacity	0.341	12.770	**0.000*** **
F	28.070		
Adjusted R^2	0.276		
p-value	**0.000*** **		

Source: Stata output, own construction.

Table 11's F value indicates that the model is significant overall (p=0.000). The adjusted R-squared value, which indicates the extent to which the independent variable (individual change capability) in the model can account for the dependent variable (usage of AI), is 0.276. As a result, it has been shown that individual change capacity accounts for 27.6% of the employees' usage of AI. The usage of AI has been found to be significantly positively impacted by individual change capacity, as indicated by the magnitude and sign of the beta coefficient. This finding provided support for the H1b hypothesis.

Regression Analysis Testing the Relationship between Use of AI and Organizational Change Motivation

The findings of the bivariate linear regression analysis regarding whether organizational change motivation sub-dimension of organizational readiness for change predicts use of AI are displayed in Table 12.

Table 12. Regression Analysis Result for Relationship between Use of AI and Organizational Change Motivation.

Dependent Variable: Use of AI	*β*	*t*	*p*
Constant	2.348	4.583	**0.000*** **
Organizational Change Motivation	0.728	13.231	**0.000*** **
F	92.239		
Adjusted R^2	0.689		
p-value	**0.000*** **		

Source: Stata output, own construction.

The model is significant as a whole (p=0.000) based on the F value in Table 12. In the model, the independent variable (motivation for organizational change) accounts for 0.689 of the dependent variable (usage of AI), which is expressed as the adjusted R-squared value. Thus, organizational change motivation has been found to account for 68.9% of the employees' adoption of AI. It has been found that organizational change motivation significantly positively affects the use of AI, based on the size and sign of the beta coefficient. This finding provided evidence in support of the H1c hypothesis.

Regression Analysis Testing the Relationship between Use of AI and Organizational Change Capacity

The findings of the bivariate linear regression analysis on whether organizational change capacity sub-dimension of organizational readiness for change predicts use of AI are shown in Table 13.

Table 13. Regression Analysis Result for Relationship between Use of AI and Organizational Change Capacity.

Dependent Variable: Use of AI	*β*	*t*	*p*

Constant	2.883	5.102	**0.000*** **
Organizational Change Motivation	0.599	10.730	**0.000*** **
F	59.921		
Adjusted R^2	0.567		
p-value	**0.000*** **		

Source: Stata output, own construction.

The model is significant as a whole (p=0.000) based on the F value in Table 13. In the model, the independent variable (organizational change capacity) accounts for 0.567 of the dependent variable (use of AI), which expressed as the adjusted R-squared value. As such, organizational change capacity has been shown to account for 56.7% of the use of AI. It has been concluded that organizational change capacity significantly positively affects the use of AI based on the magnitude and sign of the beta coefficient. Based on this outcome, the H1d hypothesis was supported.

Regression Analysis Testing the Relationship between Use of AI and Organizational Readiness for Change

The findings of bivariate linear regression analysis on whether organizational readiness for change predicts perceived use of AI are displayed in Table 14.

Table 14. Regression Analysis Result for Relationship between Use of AI and Organizational Readiness for Change.

Dependent Variable: Use of AI	*β*	*t*	*p*
Constant	2.403	9.070	**0.000*** **
Organizational Readiness for Change	0.504	7.620	**0.000*** **
F	58.030		
Adjusted R^2	0.446		
p-value	**0.000*** **		

Source: Stata output, own construction.

The model is significant overall (p-value = 0.000) based on the F value in Table 14. In the model, the independent variable (organizational readiness for change) accounts for 0.446 of the dependent variable (use of AI), which is expressed as the adjusted R-squared value. Accordingly, it was shown that the organizational readiness for change variable could account for 44.6% of the adoption of AI. It is established that organizational readiness for change significantly improves AI acceptance and use based on the size and sign of the beta coefficient. Thus, there is support for the H1 hypothesis.

4.7 Hypotheses Decisions

Table 15. Hypotheses Results.

Hypothesis	*Decision*
H1: Organizational readiness for change has a significant positive impact on the use of AI in the Public Sector Organization of Azerbaijan.	supported

$H1_a$: Individual change motivation has a significant positive impact on the use of AI.	supported
$H1_b$: Individual change capacity has a significant positive impact on the use of AI.	supported
$H1_c$: Organizational change motivation has a significant positive impact on the use of AI.	supported
$H1_d$: Organizational change capacity has a significant positive impact on the use of AI	supported
H2: Use of AI differs according to demographic variables.	rejected
$H2_a$: Use of AI differs according to gender.	rejected
$H2_b$: Use of AI differs according to age.	rejected
$H2_c$: Use of AI differs according to marital status.	rejected
$H2_d$: Use of AI differs according to educational status.	rejected
H3: Organizational readiness for change differs according to demographic variables.	partially supported
$H3_a$: Organizational readiness for change differs according to gender.	supported
$H3_b$: Organizational readiness for change differs according to age.	rejected
$H3_c$: Organizational readiness for change differs according to marital status.	rejected
$H3_d$: Organizational readiness for change differs according to educational status.	supported

Source: Own Construction.

5. Conclusion

The research findings concentrate on relationship between organizational readiness for change and employing Artificial Intelligence (AI) in Public Sector Organization of Azerbaijan through the employment of a quantitative method, taking into account individual and organization motivation for change along with their capacity of it.

The study shows that there is a positive correlation between organizational readiness for change and the use of AI, which implies that organizations which are more prepared for change have higher chances to accept and efficiently apply AI technologies. The use of AI is strongly influenced by individual and organizational change motivation and capacity. The relationship between these factors plays a crucial role in the effective adoption of AI technologies within Public Sector Organization contexts. The research also looks into if there are differences in organizational readiness for change and the adoption and use of AI according to demographic variables.

Performing the regression analysis on our developed hypotheses, the results confirm that readiness of an organization for change positively affects using AI and supports the significance of individual motivation and capacity to change, as well as those from a group's perspective - all are critical elements affecting how quickly people adopt applications related to artificial intelligence. The regression results enlighten our comprehension on the various variables that influence AI's use in organizations, such as its relationship with organizational readiness for change and motivations and capacity towards change among both individuals and organization.

The results from the study are in line with the theoretical framework because they correspond to the theories that were discussed within the scope of reseach, particularly Technology Acceptance Model (TAM). According to TAM, a person's belief about how useful and easy-to-use technology is plays an important role in their acceptance of it. The findings of the study confirm the idea of the concept by demonstrating that when workers perceive AI as beneficial and simple to operate, they are more inclined towards accepting its presence at their work. The study examines how demographic variables influence the acceptance and use of AI, which is similar to TAM's expanded models that consider social influence and cognitive tools as external features in technology acceptance.

Moreover, the study's focus on an organization's readiness for change aligns with TAM's emphasis on the surrounding environment when technology is deployed. It hints that organization's motivation and capacity to change may affect how well it adopts AI, which is akin to how TAM2 includes factors such as personal norms and voluntariness. The study results about using AI in public relations as a tool and what affects its acceptance aligns with TAM, highlighting readiness at individual and organizational level during accepting new technology. The study broadens the TAM with the application of AI in public sector.

Alignment of study results with Technological Readiness Index (TRI) means there is a significant likeness in comprehending the way Artificial Intelligence (AI) is adopted and used among public sectors. TRI verifies if people could accept new technologies by arranging their technology attitudes into groups such as optimism, innovativeness or discomfort/insecurity. Such different stances towards technology play an important role in deciding if someone is ready for it or not which then affects the possibility to use AI directly. The study results align with the TRI concept, indicating that readiness of the organization for change - encompassing personal and group motivations towards change alongside capacity to execute it - has a positive impact on AI utilization, which implies that if people and groups are more prepared for changes, an optimistic attitude about technology shown in higher scores of both optimism and innovativeness could potentially increase their chances of accepting uses related to AI and gaining benefits from it.

Moreover, when examining regression in the study, we find that change motivation at an individual level is a significant determinant of AI usage. This aligns with TRI's emphasis on personal technology attitudes: being more motivated and innovative might result in increased acceptance and use of AI by Public Sector Organization due to better change readiness. The results from this research also show how much attributes such as gender or educational status can influence readiness for change within an organization, therefore affecting the adoption rate of AI. This further emphasizes the role played by individual features in technology's readiness and acceptance.

Additionally, the results of this study align with Theory of Reasoned Action's focus on attitude towards behavior. Here, a positive evaluation for behavior (in our case – use of AI) raises chances of action. The substantial positive effects discovered in the regression analysis confirm this idea that having a favorable attitude generates stronger intention to use AI. As per Theory of Reasoned Action, subjective norms or the observed social pressure to undertake a behavior is also instrumental in creating behavioral intentions. The study's hypotheses that were supported mean beliefs regarding AI benefits, like better performance and efficiency, will probably result in its acceptance and use. This aligns with the Theory of Reasoned Action stating that behavioral beliefs impact attitudes and then behaviors.

Based on the findings of the study, the following recommendations can be given to the public organizations in Azerbaijan:

- Improve the psychological and behavioral preparedness of the organization to implement AI-related changes effectively.
- Encourage optimism and innovativeness among employees to increase their propensity to use and adopt new technologies.
- Provide training and support to reduce discomfort and insecurity related to technology among employees.
- Utilize the demographic data to tailor change management strategies, as differences in organizational readiness and AI adoption may exist across gender and educational levels.

For future studies, the research scope must be expanded to include more varied Public Sector Organization organizations from different regions. This will give a more comprehensive view of how AI is adopted and the difficulties it encounters in various cultural and administrative environments. Furthermore, there is a requirement for profound qualitative analysis.

Qualitative methods like in-depth interviews or case studies might bring out a deeper comprehension of the intricate elements connected to AI use within public organizations. This understanding could reveal unique difficulties and opportunities which quantitative analysis alone may not display. The cultural and behavioral aspects that impact AI adoption is very important. The study about organizational culture and workers' attitudes towards AI would be very helpful. If we can understand how these things interact, it might assist us in making particular plans that produce an auspicious setting for technological change. This could improve possibilities of accepting AI successfully and realizing its full capacity within Public Sector Organization service.

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Appendix

Table 16. Statements Used to Measure Organizational Readiness for Change Scale.

1. Even when the organizational change requires me to complete new tasks, I am confident that I will do this well.
2. I have a positive feeling about new organizational changes being implemented.
3. I don't feel scared or alarmed by new organizational change.
4. I believe that this organizational change is needed for our organization.
5. I have the capacity to efficiently carry out the organizational change tasks given.
6. The organizational change in our organization leads to an increase in my individual job performance.
7. I know what is needed to prepare for the relevant organizational change.
8. I have the content-specific knowledge required for the relevant organizational change
9. I have the specific technology required for this organizational change.
10. I have the typical set of skills needed to implement this organizational change.
11. I daringly invest resources and time in the new organizational change.
12. When required for the success of the organizational change, I can undertake personal sacrifices.
13. The members of our organization have collectively developed the confidence that our organization is capable of such changes.
14. The members of our organization share and interpret the organizational change in a positive manner.
15. The members of our organization do not fear the planned organizational change.
16. The members of our organization believe that the new organizational change is optimal for improving the current situation.
17. The members of our organization believe that our organization has great capacity to accept and implement this organizational change.
18. The members of our organization believe that the organization will benefit from this change.
19. The individual and departments' roles and tasks for organizational change have been distributed evenly.
20. The structure of the organization is compatible with the successful acceptance and implementation of this organizational change.
21. Our organization has adequate resources (human, physical, financial) to carry out this organizational change.
22. The objective of the organizational change is clear.
23. Our organization explains, in detail, the contents related to organizational change.
24. Our organization is capable of providing the physical and psychological rewards for the long/short-term success of the organizational change.
25. The CEO continuously emphasizes the importance of organizational change.
26. The executives and managers lead by example to promote organizational change.
27. The members of our organization are open-minded to the relevant organizational change.
28. The members of the organization cooperate with each other to promote the acceptance and implementation of organizational change.

Table 17. Statements Used to Measure the Use of AI scale.

29. The organization has implemented AI in all processes.
30. The use of AI had a high impact on operations.

31. The adoption of AI, considering its potential for the organization, was an extensive process.
32. The AI implementation changed processes substantially.

Figure 9. Gender Statistics.

Source: Google Forms.

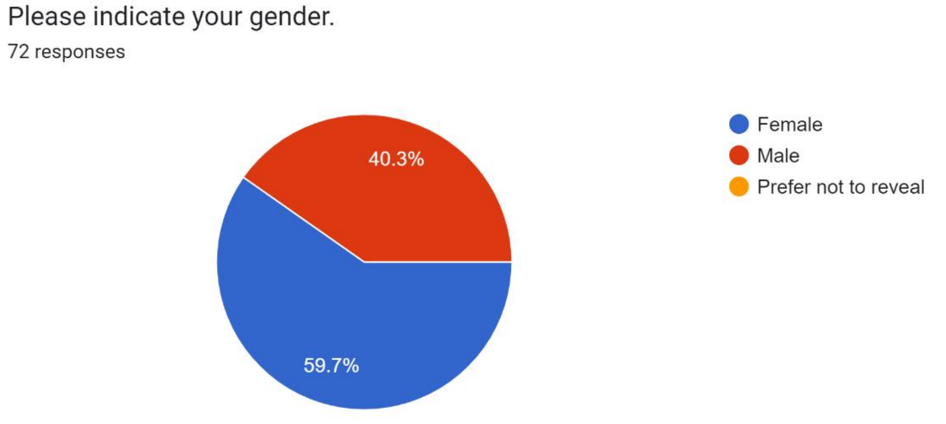
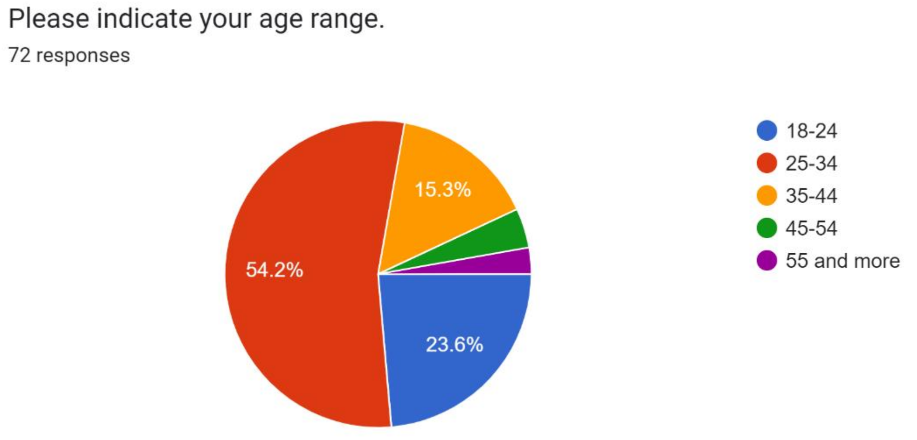
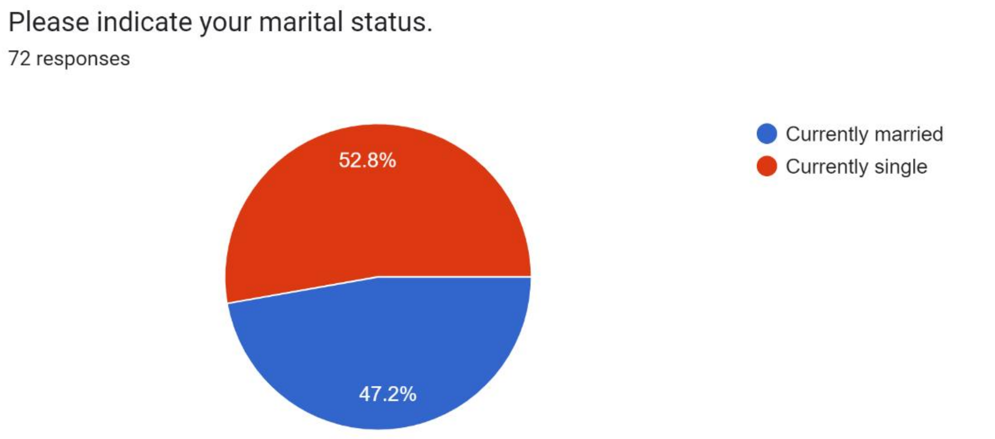


Figure 10. Age Statistics.



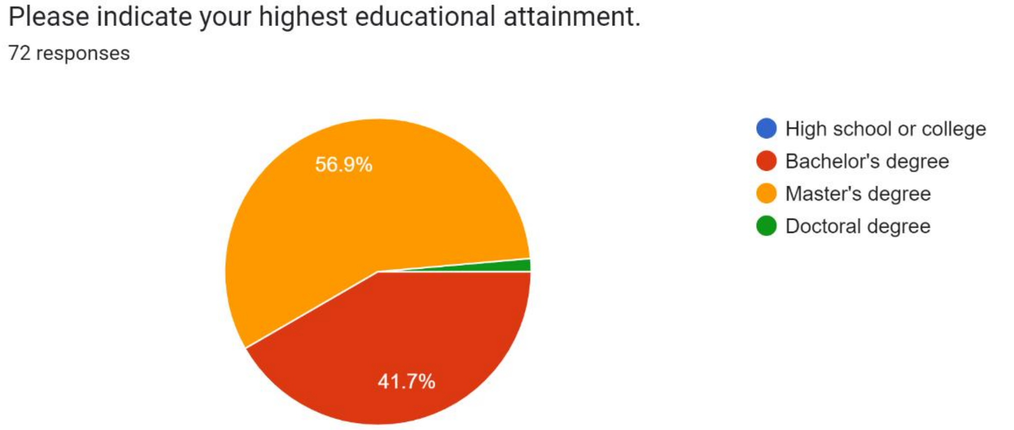
Source: Google Forms.

Figure 11. Marital Status Statistics.



Source: Google Forms.

Figure 12. Educational Background Statistics.



Source: Google Forms.

Resümee

ORGANISATSIOONI VALMISVALMISTUSE MÕJU TEHISINTELLEKTI KASUTAMISE MUUTMISEKS: AVALIKS SEKTORI JUHTUM AZERBAIDŽAANIS

Nazrin Mehdizade

Uurimus uurib, kuidas organisatsiooniline valmisolek muutusteks mõjutab tehisintellekti (AI) kasutamist ja aktsepteerimist Aserbaidžaani avalikus sektoris. Uuringus käsitletakse digitaalset transformatsiooni, selle tegevuskava ja sellega seotud strateegiaid, keskendudes inimteguritele ja tehisintellektile. Selles vaadeldakse erinevaid teooriaid, mis on seotud organisatsiooniliste muutuste ja tehnoloogia aktsepteerimisega, nagu põhjendatud tegevuse teooria ning adopteerimise ja leviku teooria. Uuringus kasutatakse kvantitatiivset meetodit organisatsiooni muutusteks valmisoleku ja tehisintellekti kasutamise vahelisi seoseid uurides, võttes arvesse demograafilisi muutujaid kui võimalikke mõjutajaid. Selles uuringus kasutatakse skaalasid, et hinnata nii organisatsiooni valmisolekut kui ka tehisintellekti kasutamist, teostada faktori- ja regressioonianalüüse, et teha kindlaks individuaalsete ja organisatsiooniliste muutuste motivatsioonide tähtsus ning tehisintellekti kasutuselevõtu võimekus. Tulemused näitavad, et tehisintellekti kasutamist mõjutavad nii üksikisiku kui ka organisatsiooni valmisolek, kusjuures sellised aspektid nagu vanus, sugu ja haridustase mängivad rolli muutusteks valmisoleku arusaamade kujundamisel. Need tulemused on kooskõlas olemasolevate teooriatega. Nad rõhutavad tehisintellekti tõhusaks integreerimiseks tehnoloogiasse positiivse suhtumise ja organisatsioonide julgustava kultuurilise õhkkonna tähtsust. Uurimistulemused keskenduvad organisatsiooni muutusteks valmisoleku ja tehisintellekti (AI) kasutamise vahel Aserbaidžaani avaliku sektori organisatsioonis tööhõive kaudu. kvantitatiivset meetodit, võttes arvesse individuaalset ja organisatsiooni motivatsiooni muutusteks ning nende suutlikkust seda teha.

Uuring näitab, et organisatsiooni muutusteks valmisoleku ja tehisintellekti kasutamise vahel on positiivne korrelatsioon, mis tähendab, et muutusteks rohkem valmis olevatel organisatsioonidel on suurem võimalus AI-tehnoloogiaid aktsepteerida ja tõhusalt rakendada. Tehisintellekti kasutamist mõjutab tugevalt individuaalne ja organisatsiooniline muutuste motivatsioon ja suutlikkus. Nende tegurite vaheline seos mängib AI-tehnoloogiate tõhusal kasutuselevõtul avaliku sektori organisatsioonide kontekstis üliolulist rolli. Samuti uuritakse, kas organisatsiooni muutusteks valmisolekus ning tehisintellekti omaksvõtmises ja

kasutamises on erinevusi vastavalt demograafilistele muutujatele. Uuringu tulemuste põhjal saab Aserbaidžaani avalik-õiguslikele organisatsioonidele anda järgmised soovitused:

• Parandada organisatsiooni psühholoogilist ja käitumuslikku valmisolekut tehisintellektiga seotud muudatuste tõhusaks rakendamiseks.

• Julgustada töötajate seas optimismi ja uuendusmeelsust, et suurendada nende kalduvust uute tehnoloogiate kasutamiseks ja kasutuselevõtuks.

• Pakkuda koolitust ja tuge, et vähendada tehnoloogiaga seotud ebamugavust ja ebakindlust töötajate seas.

• Kasutage demograafilisi andmeid muudatuste juhtimise strateegiate kohandamiseks, kuna organisatsioonilises valmisolekus ja tehisintellekti kasutuselevõtus võib esineda erinevusi soo ja haridustaseme vahel.

Edaspidiste uuringute jaoks tuleb uurimisulatust laiendada, et hõlmata mitmekesisemaid avaliku sektori organisatsioonide organisatsioone erinevatest piirkondadest. See annab põhjalikuma ülevaate tehisintellekti kasutuselevõtust ja raskustest, millega see erinevates kultuuri- ja halduskeskkondades kokku puutub. Lisaks on nõutav põhjalik kvalitatiivne analüüs. Kvalitatiivsed meetodid, nagu süvaintervjuud või juhtumiuuringud, võivad tuua sügavama arusaamise AI kasutamisega seotud keerukatest elementidest avalikes organisatsioonides. See arusaam võib paljastada ainulaadseid raskusi ja võimalusi, mida kvantitatiivne analüüs üksi ei pruugi näidata. Tehisintellekti kasutuselevõttu mõjutavad kultuurilised ja käitumuslikud aspektid on väga olulised. Uuring organisatsioonikultuuri ja töötajate suhtumise kohta tehisintellekti oleks väga kasulik. Kui suudame mõista, kuidas need asjad omavahel suhtlevad, võib see aidata meil koostada konkreetseid plaane, mis loovad soodsa keskkonna tehnoloogilisteks muutusteks. See võib parandada võimalusi tehisintellekti edukaks vastuvõtmiseks ja selle täieliku võimsuse realiseerimiseks avaliku sektori organisatsiooni teenuses.

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