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A Study on the Relationship between Employees' Attitude towards Artificial Intelligence and Organizational Culture

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Author's contribution

The sole author designed, analysed, interpreted and prepared the manuscript.

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ABSTRACT

The aim of this study is to examine whether there is a statistically significant relationship between employees' general attitudes to artificial intelligence and organizational culture. For this purpose, quantitative methodology and correlational survey design was used. The sampling method was purposive sampling as the research had a specific target group. Participants of this research were so-called white collars working at an organization in Aksaray city, Turkey. The results demonstrated that employees' general attitudes towards AI differ in terms of demographic variables. Also, it was found out in the study that there is a significant positive relationship between attitudes towards AI and organizational culture. Specifically, the results revealed that clan culture, market culture and hierarchy culture have a positive impact on the attitude towards AI.

Keywords: Artificial intelligence; organizational culture; attitude; technology adoption.

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1. INTRODUCTION

The Fourth Industrial Revolution is considered to be close right now and it has already started to alter the course of human history. The Fourth Industrial Revolution, led by artificial intelligence (AI), was declared at the 46th World Economic Forum, which took place in Davos, Switzerland, in January 2016. Additionally, the report "The Future of Jobs" suggested that this revolution would change the nature of employment [1,2]. Since Turing, AI has advanced tremendously, and in the modern era, the availability of large data, the growth of Cloud computing, related computing, storage capacity, and machine learning (ML) have significantly boosted the effectiveness and impact of AI. Today, using AI in many aspects of our daily life has become second nature, including language learning, robotics, computer vision, and self-driving cars [3,4]. Even further, according to one future projection, in addition to the Chief Innovation Officer (CIO), the successful companies during the AI revolution will also need to appoint a Chief Artificial Intelligence Officer (CAIO), who will be in charge of assessing and utilizing AI technologies to get the most out of their implementation in all areas of the company [5].

By definition, revolutions include significant modifications. The Industrial Revolution brought about the large, industrial company that utilized the power of machines to replace, supplement, and amplify the manual labor performed by humans. This significantly increased productivity and provided consumers with affordable products, greatly expanding the market and raising living standards. The digital revolution made use of computers' ability to replace, enhance, and complement the normal mental processes carried out by people. This increased productivity and further lowered costs. As was already noted, the AI revolution seeks to replace, enhance, and complement nearly every work currently carried out by humans, effectively making them a serious rival for the first time [5].

Numerous terminology, such as intelligent software agent systems, expert systems, intelligent executive systems, knowledge-based systems, etc., are used to describe AI-based systems. Big Data and Advanced Algorithms have made AI more widely used as an integrated component of digital systems today. In conclusion, researchers who have looked into the implications of AI for decision making have focused a lot of attention on the impact that AI has on human decision making [6]. Everyone is in agreement that the increasing use of AI will present special ethical, legal, and philosophical issues that must be resolved. In a world with self-driving automobiles, these challenges will actually require decisions from robots and, consequently, their human programmers. Numerous people, including influential figures like Mark Zuckerberg, have called for regulation in response [7]. Therefore, it is inevitable that AI is going to have an influence on employee behaviours. That is why companies should possess an organizational culture which encourages the adoption and use of AI in the organizational setting.

Organizational culture is primarily determined by common norms (i.e., what attitudes and actions are permissible at the organization?) and shared values (i.e., what is essential in the organization?) [8]. Based on this perspective, the attitudes of employees towards AI is of utmost importance for organizations. Employees' positive or negative attitudes towards AI within the organizational culture will have a great impact on how fast the organization will adopt AI technologies and start to utilize them. Therefore, it has become an urgent need in the literature to investigate the relationship between organizational culture and attitude towards AI in the organizational context. Within this context, this study examines the relationship between employees' attitudes towards AI and organizational culture. The paper consists of theoretical background, methodology, findings, discussion and conclusion parts.

2. THEORETICAL BACKGROUND

2.1 Artificial Intelligence (AI)

In 1956, Marvin Minsky and John McCarthy, a computer scientist at Stanford, hosted the roughly eight-week-long Dartmouth Summer Research Project on Artificial Intelligence (DSRPAI) at Dartmouth College in New Hampshire, which is when the term "artificial intelligence" was first used [7]. Artificial intelligence (AI) is defined as "a broad set of methods, algorithms, and technologies that make software 'smart' in a way that may seem human-like to an outside observer" [9]. According to Dowell [10] and Puaschunder [9], AI is viewed as a cutting-edge technology or as the culmination of numerous technological advancements that are the exclusive property of the private, technological sector.

Since its establishment as a field of study in the 1950s, artificial intelligence has been mostly ignored by scientists and has received little practical attention. Today, Big Data has become a topic of discourse in both the business world and the general public as a result of its growth and advancements in computer power. According to the sorts of intelligence it demonstrates (cognitive, emotional, and social intelligence), AI can be categorized into analytical, human-inspired, and humanized AI, or into Artificial Narrow, General, and Super Intelligence according to its evolutionary stage [7]. Artificial intelligence (AI) is the ability of machines to adapt to new situations, deal with unforeseen circumstances, solve problems, provide answers, devise plans, and carry out a variety of other tasks that call for a level of intelligence typically present in human beings. AI is currently evolving into a crucial factor in the realms of technology, commerce, and politics. The interaction between humans and AI will most likely define the course of the Fourth Industrial Revolution [11].

Academic researchers have returned to the study of artificial intelligence (AI) in the last fifty years. Making a machine behave in ways that would be considered intelligent if a human being did so is what the Dartmouth Research Project identified as AI. Although connected, the Internet of Things (IoT) and Big Data are distinct concepts from artificial intelligence (AI). While Big Data comprises all data gathered, the IoT allows the acquisition of external data to be used as AI input. Furthermore, since humans "have cognitive, emotional, and social intelligence," intelligent systems may accurately mimic these traits in human behaviour. Similar to this, there are other approaches to access AI and machine learning [12]. In spite of this, the goal is to deliver and manage intelligent goods, services, and experiences through sharing information in order to work together or produce the most possible value [13]. Though AI is still in its infancy, it is challenging to forecast what will happen to it in the future. AI has altered more than only how information is produced and used in decision-making. A number of industries that provide increasingly competitive and sustainable goods or services have been impacted by AI's revolution in business methods [14,6].

Although the successful companies in the AI era in 2037 cannot be anticipated, they are likely to be more digital than traditional. To create, produce, and market their goods and services, they will fully take advantage of global prospects, and in order to innovate and expand, they must be ready to take on business risks. Because breakthrough ideas can come from anywhere and because crowd sourcing and venture capital will make it easier to develop and finance them, the speed of technological change brought on by the coming AI revolution will create enormous opportunities for growth and profitability as well as new challenges and competition from new garage type start-ups [5]. According to Hawking and colleagues, "The biggest event in human history would be the success in developing AI. Unfortunately, unless we learn how to minimize the risks, it might also be the last [15,16].

2.2 Attitude towards AI

According to Fishbein and Ajzen [17], attitude is the latent disposition or propensity to react favorably or unfavorably to a psychological object. Any discernible feature of an individual's environment, including a behaviour, can serve as the attitude object. This definition has two characteristics that are noteworthy. First, attitudes are inherently evaluative in that they assign people a position on a single, unitary evaluative dimension with respect to an object, a dimension that might range from neutral to positive. Today's definition of attitude is a "psychological tendency, expressed by evaluating a particular entity with some degree of favor or disfavor" [17]. According to the conventional definition, attitude is made up of three complementing elements that do not compete with one another: (i) The cognitive component denotes the content of one's thoughts, such as one's beliefs about what constitutes a fact. (ii) The emotional component denotes the positive-negative emotional relations or feelings one has toward an object or activity. (iii) The behavioural component denotes the action tendencies one has to respond to an object in a particular way [11].

People express their feelings in order to engage in a desired behaviour, whether it is positive or bad. The sense of attitude is covered by this [18]. According to the Technology Acceptance Model (TAM) theory put forth by Davis and colleagues, a person's attitude toward using a system serves as a proxy for their behavioural intention. Studies support the theory put out by the Theory of Planned Behaviour (TPB) that users' attitudes affect their behavioural intentions. According to numerous additional studies [19,20], attitude serves as a potent mediation variable to explain behavioural intention.

The theory of reasoned action (TRA), the theory of planned behaviour (TPB), and the technology acceptance model (TAM) are useful for examining attitude as a factor in the application of new technologies. According to TRA, one's attitude toward a specific activity and the arbitrary standards that govern it may encourage or dissuade one from engaging in that conduct. TPB augments the two variables influencing intention in TRA by adding perceived behavioural control. The TAM takes into account perceived usefulness (defined as "the prospective user's subjective probability that using a specific application system will increase his or her job performance within an organizational context") and perceived ease of use (defined as "the degree to which the prospective user expects the target system to be free of effort"); both influence attitude and behavioural intention [11].

According to Fishbein's theory of attitude, the following steps are involved in the development of an attitude: (1) A person has a variety of ideas about a certain thing, and that thing may be connected to a number of different things, such as other things, traits, objectives, etc. (2) An implicit evaluative reaction, or attitude, is connected to each of the qualities. (3) The evaluative reactions are connected to the attitude object by conditioning. The conditioned evaluative reactions add up, so (5) the attitude object will in the future elicit this summarizing evaluative response, or the overall attitude [18].

The quest to anticipate and understand social behaviour has focused more on attitude than any other psychological concept. In a wide variety of contexts, including organizational behaviour, political behaviour, and racial discrimination, attitudes have been used to explain behaviour. Social psychologists have put a lot of effort into theories of attitude formation and modification, attitude assessment, and the relationship between attitudes and behaviour over the years [17].

The development of AI technology began in the 1940s and 1950s, but it did not realize its full potential until the 21st century. Particularly from the 2010s to the present, it has shown an exponential rise in both computational power and popularity [21]. The improvement of AI technologies gradually gave rise to concerns about unemployment among employees in various sectors throughout the world. In fact, technology-related unemployment anxiety is nothing new. It first appeared during the early industrial era's Luddite movement and has since come back on occasion. For instance, John Maynard Keynes projected in 1930 that machines would eliminate labour in two generations. The same thing was said about computerization in the 1980s and 1990s, despite the more upbeat claims of others who spoke of a massive "upskilling revolution" with the advent of post-industrialism [22]. Recent critics, however, assert that the situation is fundamentally different today and foresee the widespread demise of the workforce. There will be a "second machine age" in the twenty-first century, in which cognitive and non-routine jobs, particularly those that were originally thought to be beyond the scope of mechanization, will be replaced by artificial intelligence (AI) [12,23].

An additional issue in many organizations' transformation efforts is the expanding usage of AI. Because they recognize the opportunities presented by modern technologies, some employees are willing to accept the newest solutions in this area. Contrarily, many other workers are hesitant to embrace new technology advancements and may even be afraid of them. Some of this skepticism and anxiety stems from science fiction ideas that, in the future, robots would kill people and take over the planet. In addition, workers' worries about losing their employment because technology may eventually replace people in the workforce are another source of negative attitudes about AI [24,25].

When it comes to the adoption of new technologies, employee attitudes are crucial. This subject has been the subject of a sizable body of research. According to the technology acceptance model, a number of factors, such as how valuable a new technology is seen by employees, influence whether or not a company decides to adopt it. Employee attitudes about technology are influenced by a number of variables that are related to the new technology, the employee, the human-machine interface, as well as other areas. Beyond the overall significance of employee attitudes, not-invented-here attitudes—which refer to unfavorable views regarding obtaining technology from outside sources—are well known [25,26]. Positive attitudes may be important in certain circumstances at this stage of evolution, although negative attitudes are more common in corporate settings. Many CEOs struggle to change employees' negative views to neutral or AI attitudes [25].

78 research publications on AI, people, and trust were surveyed for the Partnership on AI's Human-AI Collaboration Trust Literature Review. Overall, they discovered that while there is broad agreement that how much confidence people have in artificial intelligence (AI) depends on the context, the literature seems to make the oversimplified assumption that AI explanations "will demonstrate trustworthiness, and once understood to be deserving of trust, people will use AI" [27].

According to a Boston Consulting Group (BCG) poll of 14,000 internet users from around the world, respondents were comparatively more in favor of using AI in sectors including traffic and transportation, public infrastructure, and customer service. The application of AI in settings involving criminal justice has seen the most opposition [28]. These polls also point out important racial and personal characteristics that affect support for AI. The BCG poll reveals that younger respondents and respondents who resided in metropolitan regions supported AI more than their older or more rural colleagues, in line with research on technology adoption more generally [27].

2.3. Organizational Culture

The term “organizational culture” is one of the most investigated topics in the organizational behaviour literature. Over 4,600 research publications concerning organizational culture have been published by academics [29,30]. The history of culture as a notion is lengthy and complicated. The term has gained popularity among people who use it to denote refinement, like when we say that a person is very "cultured." Anthropologists have used term to describe to the traditions and rituals that cultures establish over their history. Some organizational scholars and managers have used it to refer to the culture and procedures that organizations establish around how they treat their employees or to the organization's stated principles and credo over the course of the last few decades. [31]. With the understanding of the importance of human resources - intellectual capital - over time, the concept of culture entered the management literature in the last quarter of the 1900s. The concept of culture, which is mentioned in the sociology and anthropology literature, entered the management literature with Pettigrew's article "A study on organizational cultures" in 1979, and its definition, dimensions and methods have been at the centre of research and discussions since then [32]. Culture is both a dynamic reality that is always present, continually performed and generated by our interactions with others, and affected by leadership behaviour [31]. It is also a set of routines, structures, rules, and conventions that serve to both direct and restrain conduct.

Although it is one of the most popular and intensively studied topics in the management and organization literature, there is no consensus on the definition of organizational culture as a concept, the determination of its boundaries and components, its features and functions. Many definitions of the concept of culture -due to its dynamic nature- and giving various meanings by many disciplines can be counted among the reasons for this situation. While Hofstede defines culture as the common programming of the mind that distinguishes a group of people from others; House et al. defined as shared values, attitudes, beliefs, interpretations, and significant events that arise from the common experiences of members of a community and are passed on through generations [32,33,34]. It is accepted that the concept of organizational culture was first comprehensively discussed and discussed in the field of management and organization in the article titled "On Studying Organizational Culture" written by Andrew Pettigrew in 1979 [35]. The concept of culture was first used by Edward Taylor in 1871. Culture, as a concept taken from anthropology, began to be referred to as organizational culture with the new qualities it gained in businesses, and Elliott Jaques used this concept for the first time in 1952 with his book "The Changing Culture of a Factory" [36].

The four characteristics that make up Cameron and Quinn's organizational culture dimensions are clan culture, adhocracy culture, hierarchical culture, and market culture. Different internal principles govern each dimension. Clan culture emphasizes the values of dedication, participation, cooperation, and family; adhocracy culture emphasizes innovation, risk-taking, and creativity; hierarchical culture emphasizes efficiency; and market culture emphasizes competition, surroundings, and interaction. Teamwork, employee engagement programs, and corporate commitment of employees are typical traits of a clan culture as opposed to the guidelines and procedures of a hierarchy culture or the aggressive profit centers of a market culture. Unlike hierarchies, adhocracy cultures do not prioritize power or authority relationships. Instead, power shifts from one person to another or from one task team to another, depending on the issue at hand. Innovation, originality, and taking risks are the concepts that are emphasized in adhocracy culture [37].

Numerous definitions of organizational culture have been put out in the literature on organizational behaviour. For instance, corporate culture was described by Kilmann and colleagues as "the shared philosophies, ideologies, values, assumptions, beliefs, expectations, attitudes and norms" that bind a firm. Deal described it as "the human invention that creates solidarity and meaning and inspires commitment and productivity." It is described as a "system of shared values (what is important) and beliefs (how things work) that interact with a company's people, organizational structures, and control systems to produce behavioural norms" by Uttal [38,39]. Robbins defines organizational culture as the system of values shared among employees and the main feature that distinguishes a business from other businesses. Organizational culture also shapes the identities of its members. Organizational culture consists of a set of assumptions learned by a certain group during both its adaptation to the environment and its internal integration, which have yielded positive results at an acceptable level of validity, and are therefore shown to new members as the correct way to perceive, think and feel the programs [40].

Cameron and Quinn explain the cultural structure in institutions with four different cultural structures. These 4 different cultures; human relations and development (clan) culture, bureaucracy (hierarchy) culture, market culture and adaptation to the external environment (adhocracy) culture [40]. Schein explains the formation of organizational culture with three basic factors: the beliefs, values and assumptions of the founders of the organization, the learning experiences of the employees of the organization, and the new beliefs, values and assumptions brought by new members and leaders joining the organization. Mintzberg states that organizational culture consists of three interrelated stages. These stages are the mission stage, the mission development stage and the organizational personality stage [41].

Organizational culture, which is an important concept in organizational behaviour studies; It is defined as the social and normative values and beliefs shared by organizational members that hold an organization together. Culture is a concept that has been widely researched in the literature, especially in the field of sociology and anthropology. In its simplest definition, it is commonly shared values, beliefs, ceremonies, thoughts and lifestyle. Culture includes all elements of man's past, present and future. Organizational culture can be defined as the values, beliefs and hidden assumptions that organizational members have in common [36]. The main reason for the emergence of organizational culture and the increase in research on organizational culture is the economic success of Japanese companies, Japan's emergence as an economic superpower in the late 1970s and early 1980s, American companies' loss of market share in the face of the rapid rise of Japanese companies and organizational culture. is the cultural and symbolic aspect of life gaining importance day by day [41].

The points where different definitions converge can be listed as follows [42]:

- Organizational culture is the values shared by the members of the organization.
- Organizational culture is the way of doing and conducting business in the organization.
- Organizational culture distinguishes one organization from another by giving personality to organizations.
- Organizational culture is a structure consisting of dominant and shared values, stories, beliefs and slogans told within the organization.
- Organizational culture directly affects organizational success.
- Top management and leaders have a significant impact on organizational culture.

The factors that make up organizational culture are listed as values, leaders and heroes, ceremonies and symbols, stories and legends, language, customs, norms and organizational socialization [42]. A common set of values, attitudes, beliefs, and expected behaviours between members of an organization define organizational culture. The dominant organizational culture theory proposes a hierarchy of three interconnected levels of cultural indicators, which comprise (1) foundational assumptions, (2) norms and values that indicate proper attitudes and behaviours, and (3) visible objects, language, and practices

(Schein, 1985). According to Chatman and O'Reilly [8] organizational culture is primarily determined by common norms (i.e., what attitudes and actions are permissible at the organization?) and shared values (i.e., what is essential in the organization?). This definition draws on the hierarchical model of culture. Because norms set expectations about appropriateness and values give an explanation for those expectations, norms and values are intimately related. Because norms act as a social control mechanism to influence organizational behaviour, they are the most important cultural indicator. Cultural norms affect how staff members think and act [30].

3. METHODOLOGY

As the aim of this research is to examine whether there is a statistically significant relation between two variables, namely general attitudes to artificial intelligence and organizational culture, the quantitative methodology and correlational survey design was employed. Observing the two variables in their natural state for a group of people is one way to look at how they relate to (if they do) one another [43]. Keeping in mind the features of correlational survey design, two scales -The General Attitudes towards Artificial Intelligence Scale (GAAIS) and The Cameron and Quinn Organizational Culture Scale- that were explained below were handed to the participants and the data collection procedure took a month time.

3.1 Data Collection Tools

The data was collected using The General Attitudes towards Artificial Intelligence Scale (GAAIS) and The Cameron and Quinn Organizational Culture Scale. GAAIS [44] includes 20 items within two factors, positive general attitudes with 12 items and negative general attitudes with eight. The Cronbach alpha values for the two factors were 0.88 for positive and 0.82 for negative general attitudes in validation research while they were calculated as 0.84 for positive and 0.80 for negative subscales, both of which represented good internal consistency. The factor structure also revealed the similar results with validation research by Schepman and Rodway [44] as KMO was 0.90 and Bartlett's test was significant.

The Cameron and Quinn Organizational Culture Scale was developed by Cameron and Quinn [37] and consisted of four dimensions representing four potential types of organizational cultures: clan, adhocracy, market, and hierarchy, all of which included 4 items. The Cronbach alpha values for subdimensions in this research were between 0.78 and 0.90, representing a good internal consistency. The factor structure also revealed the similar results with validation research as KMO was 0.93 and Bartlett's test was significant.

3.2 Sampling and Participants

The sampling method was purposive sampling as the research had a specific target group. Participants of this research were so-called white collars working at an organization in Aksaray city, Turkey. In this respect, organizations with a potential to provide data as employing white collars were either visited personally or reached online for data collection. The information about the participants' demographics were given below in Table 1.

Table 1. Demographics of Participants

Age		**F**	**%**	**Marital Status**	**F**	**%**
Valid	25-30	225	47.2	Married	224	47.0
	31-40	125	26.2	Single	253	53.0
	41-50	88	18.4	Total	477	100.0
	51 and older	39	8.2	**Experience (years)**	**F**	**%**
	Total	477	100.0	<1	157	32.9
Gender		**F**	**%**	1-5	121	25.4
Valid	Female	196	41.1	6-10	85	17.8
	Male	281	58.9	>11	114	23.9
	Total	477	100.0	Total	477	100.0
Educational Background		**F**	**%**			
Valid	Primary-Secondary	14	2.9			
	High School	59	12.4			
	Associate	59	12.4			
	Undergraduate	238	49.9			
	Graduate	107	22.4			
	Total	477	100.0			

As Table-1 represents, a total of 477 participants provided eligible data that is appropriate for statistical analysis. Of the total, 225 participants (47.2%) are between 25 and 30 years old, 125 are (26.2%) between 31 and 40, 88 (18.4%) are between 41 and 50, and 39 (8.2%) are above 51 years old. The number of male participants (N=281; 58.9%) outnumbers female participants (N=196; 41.1%). When participants are examined in terms of their educational background, it is seen that the group with the highest rate is undergraduates (N=238; 49.9%) while it is followed by those with a graduate degree (N=107; 22.4%). Most of the participants are single (N=253; 53.0%). Participants are categorized into four depending on their experience in the current organization and their distribution is as follows: 157 (32.9%) working less than a year; 121 (25.4%) working between one to five years; 85 (17.8%) working six to 10 years, and 114 (23.9%) working more than 11 years.

4. RESULTS AND DISCUSSION

The findings regarding the research question "Does the attitude towards artificial intelligence differ significantly according to demographic factors?" are presented in the Table 2.

As shown in Table 2, the results of ANOVA comparing AI attitudes for age show that there is a significant difference between 25-30 years old white collars (X=46,36) and 41-50 years old (X=41,25) and 51 and older (X=40,10) in terms of positive attitudes (p= .041; p< .05). When it comes to negative attitudes, the difference in means of 51 years or older (X=28.33) and 25 to 30 years old (X=23.54) is significant (p= .035; p< .05). Like in the positive attitudes, the difference between 25-30 years (X=71.52) and 41-50 years (X=64.12) and 51 or older (X=62.48) is significant (p= .030); p< .05).

Table 3 shows that t-test results comparing AI attitudes for gender revealed significant differences both in subdimensions and total scores of males and females. In positive attitudes subdimension, female participants had a higher mean (X=49.45) than males (X=42.79) and this difference was statistically significant (p= .004; p< .05). On the contrary, female participants had a significantly lower mean (X=20.33) than males (X=24.16) in terms of negative attitudes (p= .042; p< .05). In terms of total scores representing general attitudes, females again had a significantly higher (p= .040; p< .05) mean (70.28) compared to males (X=66.94).

Table 2. ANOVA Results comparing AI Attitudes in terms of Age

		Sum of Squares	df	Mean Square	F	p	Source
Positive	Between Groups	222.553	3	74.184	1.083	.041*	25-30>41-50 and 51 and older
	Within Groups	32403.979	473	68.507			
	Total	32626.532	476				
Negative	Between Groups	115.377	3	38.459	1.491	.035*	
	Within Groups	12198.715	473	25.790			25-30<51 and older
	Total	12314.092	476				
Total	Between Groups	27.157	3	9.052	.224	.030*	25-30>41-50 and 51 and older
	Within Groups	19151.791	473	40.490			
	Total	19178.948	476				

**p< .05*

Table 3. T-test Results Comparing AI Attitudes in terms of Gender

		N	X	Sd	t	df	p
Positive	Female	196	49.45	8.166	-.431	475	.004*
	Male	281	42.79	8.369			
Negative	Female	196	20.33	5.066	.369	475	.042*
	Male	281	24.16	5.108			
Total	Female	196	70.28	6.545	-.266	475	.040*
	Male	281	66.94	6.217			

Table 4. ANOVA Results comparing AI Attitudes in terms of Educational Background

		Sum of Squares	df	Mean Square	F	p	Source
Positive	Between Groups	255.396	4	63.849	.931	.039*	U>P-S
	Within Groups	32371.136	472	68.583			
	Total	32626.532	476				
Negative	Between Groups	45.790	4	11.448	.440	.779	
	Within Groups	12268.302	472	25.992			
	Total	12314.092	476				
Total	Between Groups	133.443	4	33.361	.827	.509	
	Within Groups	19045.505	472	40.351			
	Total	19178.948	476				

**p< .05; U=Undergraduate, P-S= Primary-Secondary school*

As can be seen in Table 4, when participants were compared for AI attitudes in terms of their educational background, there is a significant difference (p= .039; p< .05) in terms of positive attitudes between those with an undergraduate degree (X=42.99) and those with a primary or secondary school degree (X=38.69). On the other hand, the differences in the means in terms of negative attitudes (p= .779; p> .05) and overall attitudes (p= .509; p> .05) were not significant.

Table 5 shows that the mean of single white collar participants' positive attitudes (X=44.20) is significantly higher (p= .025; p< .05) than married ones (X=40.03). Besides, participants that are single have a mean of 21.07 that is significantly (p= .043; p< .05) lower than those that are married (X=24.41). When it comes to total scores, participants with no partner (X=65.27) again have a significantly higher (p= .047; p< .05) mean than married ones (X=64.44).

As Table-6 represents, number of working years at current organization that is labeled as experience in this research is a source of significant difference in both subdimensions and total scores of AI attitudes. In terms of positive attitudes, the difference between those working less than a year (X=44.99) and those working six to ten years (X=41.11) is significant (p= .013; p< .05). Besides, the mean of workers with less than a year experience (21.10) is significantly lower (p= .018; p< .05) than those with 6-10 years (X=24.15) and more than 11 years (X=25.01). When it comes to total scores, the significant difference (p= .038; p< .05) is between again those with less than a year experience (X=66,09) and six to ten years (X=35.26).

The findings related to the research question "Is there a significant relationship between the attitude towards artificial intelligence and organizational culture?" are given in the Table 7.

Table 7 shows that three types of organizational culture, namely clan, market, and hierarchy, have statistically significant relationship with both subdimensions of AI attitudes that are positive and negative attitudes. Clan culture has low-level positive (r= .097) correlation with positive attitude and low-level negative correlation (r= - .104) with negative attitude towards AI. Market culture has low-level positive (r= .106) correlation with positive attitude and low-level negative correlation (r= - .110) with negative attitude towards AI. Similarly, hierarchy culture has low-level positive (r= .093) correlation with positive attitude and low-level negative correlation (r= - .093) with negative attitude towards AI. When it comes to correlation between total scores in organizational culture and subdimensions and total scores in attitudes towards AI, there is low-level positive correlation (r= .098) between organizational culture total score and positive attitudes towards AI; low-level negative correlation (r= - .095) between organizational culture total score and negative attitudes, and low-level positive correlation (r= .105) between total scores of the two scales.

Table 5. T-test Results Comparing AI Attitudes in terms of Marital Status

		N	X	Sd	t	df	p
Positive	Married	224	40.03	8.149	-1.538	475	.025*
	Single	253	44.20	8.370			
Negative	Married	224	24.41	4.701	.736	475	.043*
	Single	253	21.07	5.409			
Total	Married	224	64.44	6.041	-1.414	475	.047*
	Single	253	65.27	6.595			

**p< .05*

Table 6. ANOVA Results comparing AI Attitudes in terms of Experience

		Sum of Squares	df	Mean Square	F	p	Source
Positive	Between Groups	376.913	3	125.638	1.843	.013*	A>C
	Within Groups	32249.619	473	68.181			
	Total	32626.532	476				
Negative	Between Groups	123.667	3	41.222	1.599	.018*	A<C, D
	Within Groups	12190.425	473	25.773			
	Total	12314.092	476				
Total	Between Groups	122.307	3	40.769	1.012	.038*	A>C
	Within Groups	19056.641	473	40.289			
	Total	19178.948	476				

**p< .05; A= less than a year; B= 1-5 years; C: 6-10 years; D: more than 11 years*

Table 7. Correlation Analysis Results between Organizational Culture and Attitudes towards AI

		Attitudes towars AI		
Organizational Culture		**Positive**	**Negative**	**Total**
Clan	Pearson Correlation	.097*	-.104*	.043
	Sig. (2-tailed)	.034	.023	.345
	N	477	477	477
Adhocracy	Pearson Correlation	.069	-.047	.052
	Sig. (2-tailed)	.134	.309	.256
	N	477	477	477
Market	Pearson Correlation	.106*	-.110*	.050
	Sig. (2-tailed)	.021	.016	.280
	N	477	477	477
Hierarchy	Pearson Correlation	.093*	-.093*	.047
	Sig. (2-tailed)	.042	.042	.306
	N	477	477	477
Total	Pearson Correlation	.098*	-.095*	.105*
	Sig. (2-tailed)	.032	.037	.026
	N	477	477	477

**p< .05*

Table 8. Regression Analysis Results concerning Organization Culture Effect on Attitudes towards AI

	Sum of Squares	df	Mean Square	F	Sig.
Regression	4039.907	4	1009.977	7.465	.000*
Residual	36125.030	473	135.300		
Total	40164.937	477			
R= .317; R^2= .101; Adjusted R^2= .087					

**p< .05*

Research results regarding the research question "Do organizational culture and its sub-dimensions have a significant effect on the attitude towards artificial intelligence?" are presented in the Table 8.

According to regression analysis results that intend to examine if organizational culture together with its subdimensions affect general attitudes towards AI, there is a significant relation (R= .317; Adjusted R2= .087) between 3 subdimensions, namely clan, market, and hierarchy, and total scores of organizational culture and attitudes towards AI. As a result, given subdimensions and total scores of the organizational culture scale is a significant indicator of general attitudes towards AI (F=7.465; p< .05). In sum, organizational culture together with its three subdimensions explain a total of seven per cent of general attitudes towards AI.

5. CONCLUSION

As part of the fourth industrial revolution, AI technology has become more and more widespread around the world within the past few years in various sectors such as health, education, defence systems and logistics. Apart from these fields of work, business organizations are also getting their share of AI-based transformation. At this point, the adaptation and adoption process is critical for a health transformation in the organizational setting. In order for the adoption of AI to take place, the attitudes of employees towards AI technologies are crucial in behavioural terms since human beings tend to reject things or ideas which they see as negative. It is well known that attitude can be used to determine how people intend to use technology [19,20,45,46]. Therefore, it is desirable for an organization to have employees with positive attitudes towards AI so that they will accept and adopt AI technologies and practices in a faster and healthier manner. For this purpose, business enterprises must build an organizational culture which will encourage and accelerate the adoption of AI.

This study has revealed the contribution of organizational culture to the healthy adoption process of AI in business organizations. It has been found out that clan culture, market culture and hierarchy culture have a positive impact on the attitude towards AI. Within this respect, it is recommended that businesses can increase their investments in AI and related technologies, encourage the use of digital technologies based on AI in production processes, improve educational opportunities at all levels to train workers in AI, and take advantage of the data economy's potential as the real source of AI. Through the development of AI, they can contribute to the new cultural drift (CD) that strives to integrate growth and socio-environmental well-being [6]. A systems approach is required for better corporate use of AI. Managers must comprehend every participant and element of the ecosystem. Management must be aware of the effects of switching from the current systems to the new AI-based systems. Business models in every industry may be impacted by changes in AI technology within the ecosystem landscape [47].

There is a distinction between artificial intelligence and non-AI humanness in the organizational setting. When many manual and repetitive tasks are transferred to robots, value may be obtained from specific human attributes. We can already observe that even when they outperform human counsel, algorithms in finance are not always favoured. The trend of returning previously outsourced monotonous work to wealthy nations with AI hubs is already evident in the organizational setting. In the future, AI and automated control will lead to economic superiority since it will free up human beings' extra time to engage in creative endeavours. In the age of artificial intelligence, leadership and organizational behavioural understanding will likely become more important [9]. There is still plenty of leeway for small and medium businesses and start-ups to find cutting-edge AI solutions and implementations in this developing industry, even with those giant firms vying for market share in the AI-driven future economy. As acquisitions, mergers, worries about intellectual capital, and other issues in the AI community emerge, managers need to be aware of the potential implications for broader business systems [47].

The following recommendations are for practitioners who want to use AI to achieve the UN 2030 agenda [6]:

- While AI can play a variety of roles in decision-making, it should be acknowledged as a decision support tool by human decision-makers through cultural drift.
- Personal characteristics, expertise, and understanding of AI among AI users all contribute to the success of AI.
- The acceptance of AI for decision-making may differ depending on cultural and individual beliefs.

COMPETING INTERESTS

Author has declared that no competing interests exist.

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