

Artificial intelligence risks to humans

Student name/ Rakan Fahad Aloufi

University ID number/ 2021205012

Graduation Project – 1

Faculty of Management - Midocean University

Supervisor

Dr. Mona Moustafa Elashry

Faculty member- Faculty of management- Midocean University

1 st Semester- 2024

Table of contents

Chapter One:

1.1 Introduction	5
1.2 Research Problem	6
1.2.1 The theoretical gap	6
1.2.2 Empirical gaps	6
1.3 Research Significant	7
1.3.1 The theoretical significant	7
1.3.2 Empirical significant	7
1.4 Research Sub-Questions	8
1.5 Research Objectives	9
1.6 Research Hypotheses	10
1.7 Research Model	12
1.8 Empirical Study.....	13
1.9 Research Methodology	15

Chapter Two:

2.1 Abstract	17
2.2 Introduction	18
2.3 Materials and Methods	20
2.3.1 Study Design and Participants	20

2.3.2 Measures 21

2.3.3 Data Analysis 22

2.4 Results 23

2.5 Discussion 26

2.6 Conclusion 28

References list 29

Table of shapes 33

Chapter One:

General framework for the study

Introduction

During the past five decades, the dangers that many people were warning about were population explosion, the decrease in natural resources and minerals, environmental pollution, and the possibility of a nuclear war. However, today, with the tremendous development in the level of technology and its applications, the matter has turned to other dangers. Robots whose intelligence will reach a degree that allows them to outperform humans, especially with artificial intelligence capabilities, or devastating computer viruses that stop the Internet from working. Artificial intelligence is the new fad that is being talked about in all fields.

A research paper issued by experts in artificial intelligence in industrial and academic fields, entitled “Harmful Use of Artificial Intelligence: Prediction, Prevention, and Mitigation,” warned that this sector will negatively affect the human race and will at some point lead to serious damage to several sensitive aspects of its life. The study considered that “dual use” and the ability of technical devices to make thousands of complex decisions per second can be used in both extremes, either to benefit or harm people, and this depends on the person who designs the system. The experts took into account the uses of artificial intelligence that currently exist or that could be developed during the next five years, and were then divided into 3 groups: digital, physical and political.

Machines equipped with special capabilities will reach levels of intelligence that exceed human levels, enabling them to make decisions independently, without referring to any human reference. Google recently appointed an ethics council to deal with deceptive issues related to artificial intelligence and help the company confront criticism related to its deals in this field. However, in less than a week, this council began to disintegrate amid resignations from a number of its members, which could pose a threat to Google's chances of winning more military cloud computing contracts.

A number of council members, including behavioral economics expert Alessandro Acquisti, announced that he would not continue in his duties assigned to him by Google. Today, a number of employees at Google began submitting a petition to the company to oust more members of this council, amid strong opposition to the technology company's involvement in military contracts to develop weapons with artificial intelligence.

The risks of AI are great, but the use and growth of these tools is also inevitable, as the benefits go beyond simple efficiency gains and include a fairer decision-making scenario when algorithms are trained to avoid bias, while also increasing our understanding from a risk management and auditing perspective, where we should look for the key to advantage. In artificial intelligence systems. Control and governance of AI must take precedence over algorithms and efficiency. We all have a responsibility to learn more about AI risks and control those risks. The topic is not going away. Risks will continue to grow and change as the technology becomes more advanced and widespread.

Research problem

If something has a bright side, then in parallel, it also has a dark side. Likewise, artificial intelligence also has some drawbacks. Although AI is one of the most popular and demanding technologies around the world, it still has some drawbacks and problems.

The theoretical gap 1.2.1:

You need to produce new AI-powered software at a financially significant cost, as well as update existing sports software to keep up with the latest requirements, in addition to the cost of repair and maintenance. Robots are one of the applications of artificial intelligence, and they have begun to replace humans in some jobs. Likewise, for artificial intelligence applications for various writing, image editing, etc., starting from jobs, it should not appear in those digital jobs. Humans have begun to rely on artificial intelligence to perform many tasks, especially repetitive ones. They have also begun to rely on robots to complete some work, and it is expected that humans will be completely dependent on artificial intelligence in the future. It is one of the risks of artificial intelligence. Advanced AI technology needs a large amount of data for training and analysis, and this raises concerns about data privacy and its proper use. Personal data may be exploited in illegal or unethical ways, putting the rights of individuals and communities at risk.

Empirical gaps 1.2.2:

Although artificial intelligence has come a long way in the world of medicine, human monitoring is still necessary. For example, surgical robots act logically, rather than empathically. Health practitioners may observe biobehavioral observations, which can help diagnose or prevent medical complications. The integration of artificial intelligence technology is growing rapidly in education, due to its great benefits, as it improves student participation and interaction by enhancing the learning experience in different ways and directing teachers to use a more interactive educational approach. Artificial intelligence tools can also participate in evaluating students and analyzing their data to become Things are clearer in front of the teacher.

Main research question

This study addresses the following main research question:

“How does artificial intelligence affect human lives?”

Research Significant

AI is used to improve efficiency and productivity in many fields, such as manufacturing, healthcare, and marketing. For example, AI can be used to improve the accuracy and speed of manufacturing processes, to improve medical diagnosis or develop new treatments, or to improve advertising targeting.

The theoretical significant 1.3.1:

The recipe for artificial intelligence is to help save time and effort gradually, as the exercise can be performed faster and faster than a human. For example, AI can be used to prepare reports, analyze data, or provide assistance with household tasks.

Empirical significant 1.3.2:

Artificial intelligence can help improve human quality of life in many aspects, such as health care, education, and entertainment. For example, AI can be used to provide better health care, develop new ways to educate children, or create new entertainment experiences. Artificial Intelligence is a powerful technology that has the potential to significantly impact human life in many aspects. As artificial intelligence continues to develop, the importance and influence of this technology is expected to increase in the coming years.

Research Sub-Questions

What is artificial intelligence?

What are the risks of artificial intelligence on humans?

What are risks artificial intelligence in Real-life ?

Why research artificial intelligence safety?

Research Objectives

artificial intelligence is a specific branch of computer science concerned with mimicking human thinking and decision-making processes. These programs can often revise their own algorithms by analyzing data sets and improving their own performance without needing the help of a human. These are often programmed to complete tasks that are too complex for non-AI machines.

We talked briefly about real-life and hypothetical AI risks above. Below, we've outlined each in detail. Real-life risks include things like consumer privacy, legal issues, AI bias, and more. And the hypothetical future issues include things like AI programmed for harm, or AI developing destructive behaviors.

There are a myriad of risks to do with AI that we deal with in our lives today. Not every AI risk is as big and worrisome as killer robots or sentient AI. Some of the biggest risks today include things like consumer privacy, biased programming, danger to humans, and unclear legal regulation.

Not that many years ago, the idea of superhuman AI seemed fanciful. But with recent developments in the field of AI, researchers now believe it may happen within the next few decades, though they don't know exactly when. With these rapid advancements, it becomes even more important that the safety and regulation of AI be researched and discussed at the national and international levels.

In 2015, many leading technology experts (including Stephen Hawking, Elon Musk, and Steve Wozniak) signed an open letter on AI that called for research on the societal impacts of AI. Some of the concerns raised in the letter cover things like the ethics of autonomous weapons being used in war, and safety concerns around autonomous vehicles. In the longer term, the letter posits that unless care is taken, humans can easily lose control of AI and its goals and methods.

The importance of AI safety is to keep humans safe and to ensure that proper regulations are in place to ensure that AI acts as it should. These issues may not seem immediate, but addressing them now can prevent much worse outcomes in the future.

Research Hypotheses

Main hypothesis H1:

Artificial intelligence (AI) refers to computer systems capable of performing complex tasks that historically only a human could do, such as reasoning, making decisions, or solving problems

Today, the term “AI” describes a wide range of technologies that power many of the services and goods we use every day – from apps that recommend tv shows to chatbots that provide customer support in real time. But do all of these really constitute artificial intelligence as most of us envision it? And if not, then why do In this article, you’ll learn more about artificial intelligence, what it actually does, ?we use the term so often and different types of it. In the end, you’ll also learn about some of its benefits and dangers and explore flexible courses that can help you expand your knowledge of AI even further.

The first sub-hypothesis Ha:

In my view, Artificial Intelligence (AI) will be the most disruptive technology over the next decade. The quality of this technology has improved considerably in a number of areas in recent years, with all the consequences this entails. Smart software systems gain an ever better understanding of who we are, what we do, what we want and why we want it. A world full of opportunities opens up. Chatbots, smart virtual assistants and autonomous intelligence software assistants will increasingly come to our aid. AI systems will bring us prosperity, time savings, convenience, insights and comfort. We will become used to a personal assistant that is available 24 hours a day and knows what we need, before we know it ourselves. Just as it is difficult to imagine living without the Internet, a decade from now will see the same scenario in terms of your personal assistant.

Also, smart AI systems will provide us with insights that we believed would never be possible, and they will provide answers to questions the existence of which we were not aware of. AI systems are faster, are never tired, learn from examples and from each other and are considerably smarter than humans in specific domains. This is not a futuristic idea but reality.

The second sub-hypothesis Hb:

The so-called human-in-the-loop approach is especially crucial in sectors where AI-based decisions directly impact individual lives and society .These sectors include:

Education: As demonstrated by the UK, AI systems should not be solely responsible for grading assignments or predicting students’ academic performance. A human teacher’s expertise and personal understanding of their students should play a decisive role in these situations.

Healthcare: AI has made significant strides in disease diagnosis, treatment planning, and patient care. However, the potential for misdiagnosis or inadequate treatment planning due to biases or errors in AI .systems emphasizes the necessity of human professionals in the final decision-making process

Recruitment and HR: AI is increasingly being used for resume screening and predicting potential job performance. However, reliance on AI can lead to biased hiring practices, potentially overlooking candidates

with unconventional backgrounds or skill sets. A human-in-the-loop approach ensures comprehensive and fair candidate evaluation.

Finance and Lending: AI algorithms can evaluate creditworthiness, but they may inadvertently discriminate based on geographical location or personal spending habits, which can correlate with ethnicity or socioeconomic status. In such scenarios, human judgment is necessary to ensure balanced lending decisions.

Criminal Justice: AI is being used to predict crime hotspots and potential reoffending. However, bias in historical crime data can lead to unjust profiling and sentencing. Human oversight can provide more nuanced perspectives and help prevent such injustices.

Autonomous Vehicles: Though AI drives the operation of self-driving cars, it's crucial to have a human in the decision-making process, especially when the vehicle has to make ethical decisions in scenarios of unavoidable accidents.

The third sub-hypothesis Hc:

The understanding, prevention, and mitigation of harms from AI. These harms could be deliberate or accidental; caused to individuals, groups, organisations, nations or globally; and of many types, including but not limited to physical, psychological, social, or economic harms.

Artificial intelligence

Our lives:

- Schools
- the health
- industry
- commerce

Positives:

- Error-free processing
- Helps with repetitive jobs
- Always available
- Make the right decisions
- Speed of making decisions

Negative:

- High costs
- Increased unemployment
- Poor creativity
- Security and privacy risks
- Increased laziness among individuals

Empirical Study

Introduction

In 1956, at a conference at Dartmouth University, scholars formally proposed the term "artificial intelligence." That moment was the first step in a new topic of studying how machines simulate human intelligent activities. In early 2016, AlphaGo defeated the world chess champion. This event immediately aroused global interest in artificial intelligence (AI) [93]. The development of artificial intelligence has brought huge economic benefits to mankind and has benefited all aspects of life, even as it has greatly promoted social development and brought social development into a new era [57]. Many scholars started AI-relevant research since the end of 20th century [92].

AI is the general term for the science of artificial intelligence. It uses computers to simulate human intelligent behaviors and it trains computers to learn human behaviors such as learning, judgment, and decision-making [94]. AI is a knowledge project that takes knowledge as the object, acquires knowledge, analyzes and studies the expression methods of knowledge, and employs these approaches to achieve the effect of simulating human intellectual activities [19]. AI is a compilation of computer science, logic, biology, psychology, philosophy, and many other disciplines, and it has achieved remarkable results in applications such as speech recognition, image processing, natural language processing, the proving of automatic theorems, and intelligent robots [20]. AI plays an indispensable role in social development, and it has brought revolutionary results in improving labor efficiency, reducing labor costs, optimizing the structure of human resources, and creating new job demands [18].

The rest of the paper is structured as follows (Fig. 1): the origin and development of AI is addressed in Section II. Section III describes enabling drivers and technologies of AI. The research fields are depicted in Section IV. Section V illustrates the application scenarios of AI. Three logical views of AI are explained in Section VI, and Section VII summarizes the paper.

Section snippets

The origin and development of artificial intelligence

Artificial intelligence is the study of how to make computers perform intelligent tasks that, in the past, could only be performed by humans [36]. In recent years, AI has developed rapidly, and it has changed people's lifestyles [37]. The development of AI has become an important development strategy for countries around the world, enhancing national competitiveness and maintaining security [69]. Many countries have introduced preferential policies and have strengthened the deployment of key

Big data

Big data is a prerequisite for AI, and it is a core factor that promotes AI to improve recognition rate and accuracy. With the development and the wide application of the Internet of Things, the amount of data generated has increased exponentially, with a great increased annual growth rate. In addition to increasing the number, the dimensionality of the data has also been expanded [105]. These large amounts of high-dimensional data make the data more comprehensive and more sufficient to support

The expert system

An expert system is a knowledge system based on the existing knowledge of human experts. The expert system was the earliest field AI research. It is widely used in medical diagnosis, in geological surveying, and in the petrochemical industry. Expert systems usually refer to various knowledge systems [60]. This is an intelligent computer program, based on knowledge, that uses professional knowledge provided by human experts to simulate the thinking process of human experts and uses knowledge and

Application scenarios of ai

Based on the relatively mature development of technical conditions such as data, algorithms, and computing capabilities, AI has begun to truly solve problems and to effectively create economic benefits [116]. From an application perspective, industries with a good data foundation (such as finance, healthcare, automotive, and retail) have relatively mature AI application scenarios.

Three viewpoints of AI

Symbolism, connectionism, and behaviorism represent the three main viewpoints of concepts in the field of AI research. They are the most important theoretical theorems in the development of AI disciplines, and they are the theoretical foundation for the development of AI disciplines.

Conclusion

The study presents a systematic overview of AI that focuses on prospects and development, core techniques, applicable scenarios, and challenges. This paper conducts a state-of-the-art review of the extant and upcoming research on AI.

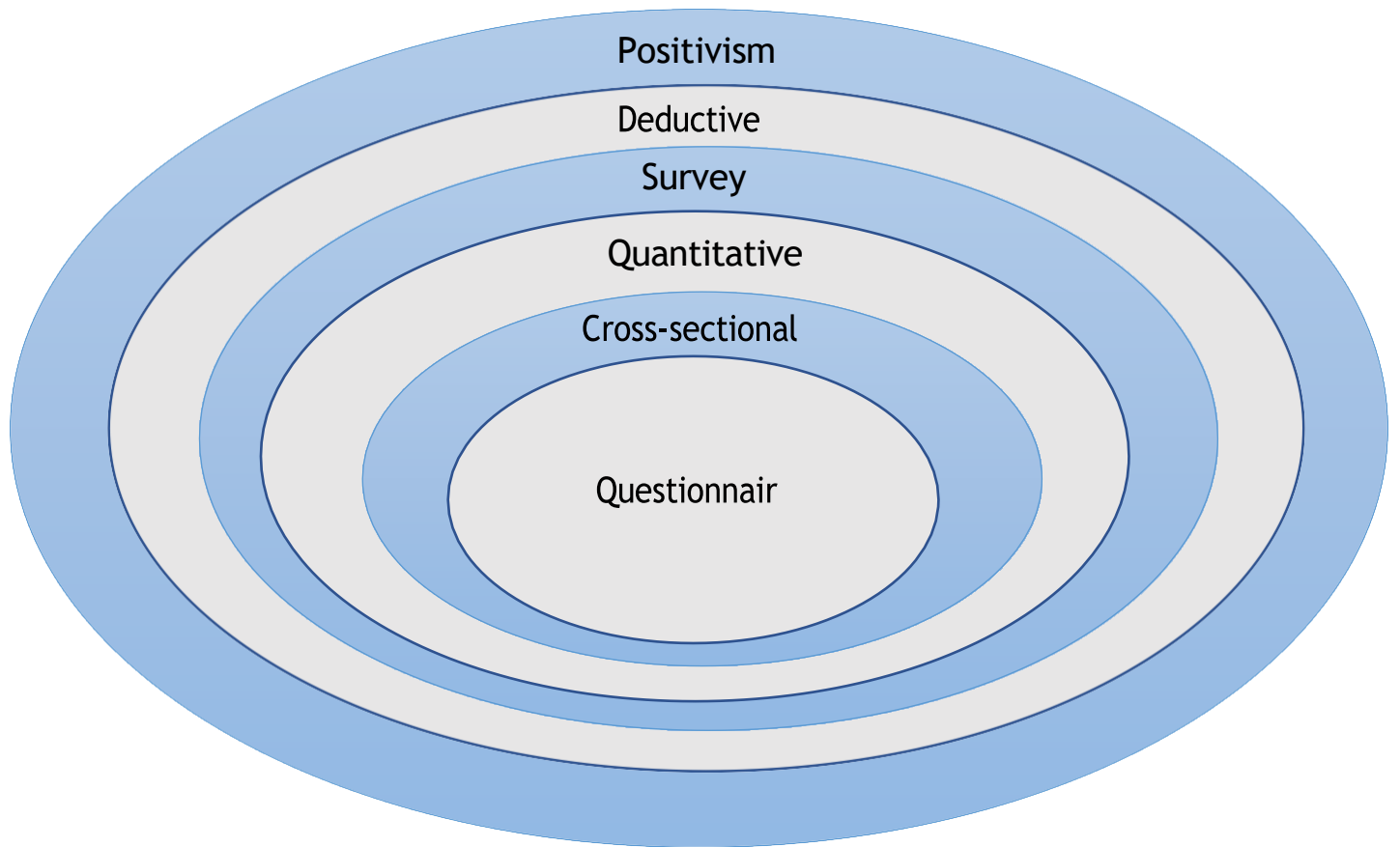
Artificial intelligence is an interdisciplinary subject that involves information, logic, cognition, thinking, systems, and biology. It has been used for knowledge processing, pattern recognition, machine learning, and natural language processing. Applications have

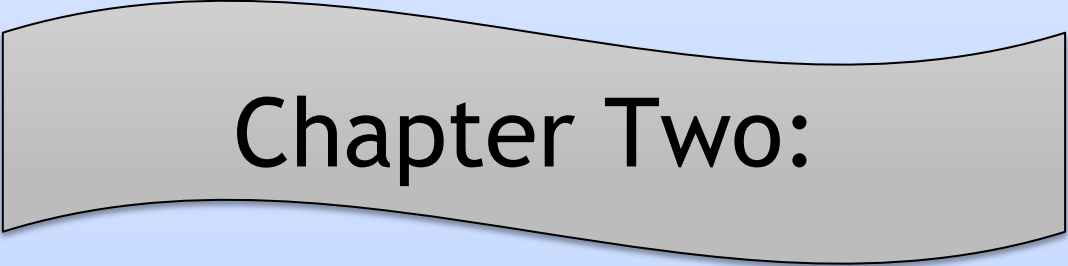
Declaration of Competing Interest

We declare that we have no financial and personal relationships with other people or organizations that can inappropriately influence our work, there is no professional or other personal interest of any nature or kind in any product, service and company that could be construed as influencing the position presented in, or the review of the manuscript entitled A review of Artificial Intelligence: The State of the Art and Future Prospects.

Acknowledgment

Funding of China National Social Science (No. 15BJY022), Funding of Researching of China University of Labor Relations (No. JG2106, No. ZYTS201806)





Chapter Two:

Theoretical framework

Artificial intelligence (AI) has become one of the core driving forces for the future development of the medical industry, but patients are skeptical about the use of AI in medical care. Based on the intergroup threat theory (ITT), this study verified that patients would regard AI as an external group, triggering the perceived threat of the external group, which results in avoidance behaviors in the treatment (experiment 1: $n = 446$) and diagnosis (experiment 2: $n = 330$) scenarios. The results show that despite AI can provide expert-level accuracy in medical care, patients are still more likely to rely on human doctors and experience more negative emotions as AI is more involved in medical care (experiment 1). Furthermore, patients pay more attention to threats at the individual level related to themselves, such as realistic threats related to privacy issues and symbolic threats related to the neglect of personal characteristics. In contrast, realistic threats and symbolic threats at the group level had less effect on patients in the medical scenario (experiment 2).

Keywords: artificial intelligence medical care, intergroup threat theory, realistic threats, symbolic threats, willingness to accept (WTA), treatment, diagnosis.

Artificial intelligence (AI) has been widely used in various medical scenarios such as prevention, diagnosis, and treatment, such as diagnosing heart disease ([Feshki and Shijani, 2016](#)), providing medical advice ([Nov et al., 2020](#)), detecting skin cancer ([Takiddin et al., 2021](#)), identifying layout lesions ([Yamashita et al., 2021](#)), and reading CT image of suspected COVID-19 cases ([Mei et al., 2020](#)), etc.

The application of AI in the medical field has become a trend. Patients are the end-users of AI health care, and their resistance will directly affect its adoption efficiency ([Agarwal et al., 2020](#)). The existing studies show that although the algorithm can be more accurate than doctors ([Grove et al., 2000](#); [Eastwood et al., 2012](#)), patients still believe that AI health care cannot provide the same quality of medical care as human doctors ([Promberger and Baron, 2006](#)) and cannot be held responsible for errors ([Eastwood et al., 2012](#)).

Psychological studies have shown that people are motivated to see their group as distinct from others ([Tajfel, 1974](#)). Human-centered attitudes generate negative perceptions of other entities, which include animals, technologies, etc. ([Kaplan, 2004](#); [Haslam et al., 2008](#)); that is, people often view other groups as threats ([Alexander, 1974](#); [Dunbar, 2013](#)). According to the intergroup threat theory (ITT), by default, humans tend to perceive threats from other groups and show hostility toward them ([Stephan and Stephan, 1985](#)). Therefore, we have a reason to believe that people tend to regard AI that does not belong to human groups as a threat, thus causing negative emotions and resistance behaviors(H1).

Furthermore, intergroup anxiety refers to negative emotions generated by interactions with external groups, such as fear, anger, disgust, and hatred. These activated negative emotions will lead to negative behaviors that include avoidance, evasion, resistance, and aggressive ([Stephan and Stephan, 2000](#)). In medical services, with the increase in AI involvement, patients will have more contact or interaction with AI that is regarded as outgroup by humans, thus leading to more intergroup anxiety and lower willingness to accept (WTA) it (H2).

Although intergroup anxiety is an important factor in explaining outgroup attitudes. But in subsequent studies, the researchers went a step further and divided the causes of humans' negative attitudes toward outside groups into the perceived realistic and symbolic threats. Realistic threats include physical harm, loss of authority, or appropriation of resources, whereas symbolic threats refer to the potential challenge to morals, beliefs, and norms caused by groups with different value systems ([Stephan et al., 2008, 2009](#)). In addition, these threats revised theory divided into group-level and individual-level threats. The former refers to the threat to the group as a whole, and the latter refers to threats to individual members of the group ([Stephan et al., 2008, 2009](#)).

Realistic individual threats concern threats of personal safety, material safety, rights, or general welfare to an individual group member ([Stephan et al., 2015](#)). As AI becomes more deeply involved in health care, more and more patients' personal biometric information is being collected. The personal information may face many potential problems, such as disclosure, misappropriation, or abuse, which poses serious privacy threats to patients and leads to lower WTA (H3).

Symbolic individual threats include the destruction of an individual's self-identity or self-esteem ([Stephan et al., 2015](#)). People have an innate desire to know themselves ([Trope, 1975](#); [Baumeister, 2010](#)) and have a perception of whether they have certain characteristics, attributes, abilities, or belonging groups ([Kettle and Häubl, 2011](#)). Thereby, when patients believe that AI medical care may ignore their characteristics and unique symptoms, they will be reluctant to use the medical services provided by AI (H4).

Realistic group threats refer to the threat to the rights, resources, and overall welfare of a group, which generally includes political power and economic power ([Stephan et al., 2015](#)). People generally regard machines as a threat to human work ([Granulo et al., 2019](#)). The existing research shows that there are concerns

about AI medical care. People worry that technology-driven productivity gains will lead to redundancies in some healthcare jobs (Hazarika, 2020). When people consider that the emergence of AI will pose a threat to their employment and even affect their future economic situation, they will perceive the group reality threat. As AI becomes more and more involved in medical care, people may worry that AI will replace part of the work of healthcare workers, thus resisting the use of AI health care (H5).

Symbolic group threats include threats to the value system, ideology, and belief system within the group (Stephan et al., 2015). It is predicted that the global AI healthcare market size is expected to grow from \$6.9 billion in 2021 to \$67.4 billion in 2027, with a CAGR of 46.2%. Key factors driving the growth of the AI healthcare market include the increase in AI tools for care, the increase in the development of AI systems for human perception, and the increasing application of AI technology such as genomics, drug discovery, imaging, and diagnostics in response to COVID-19. Therefore, the widespread use of AI technology will have a certain degree of reform on the medical system. This change will lead to patients' perception of the threat of AI medical applications and trigger resistance behaviors(H6).

In summary, we propose the research model shown in Figures 1A,B, which corresponds to the hypotheses shown in Table 1. The purpose of this study is to explore the influence of the degree of AI involvement on patients' WTA and to reveal whether the reason is caused by patients' perceived threat to outside groups. In an integrated framework of ITT, the relative influence of different levels of threat on patients' WTA AI health care is further discussed.

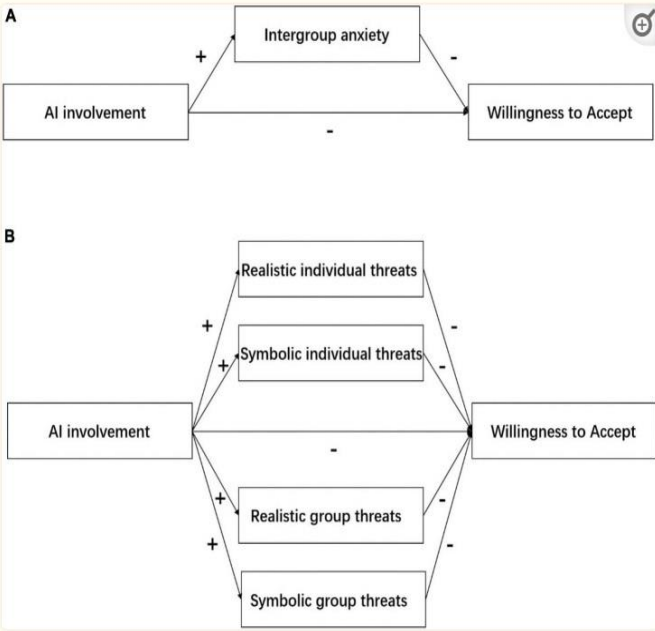


FIGURE 1
(A) The research model of experiment 1. (B) The research model of experiment 2.

TABLE 1

The hypotheses.

Hypotheses

- H1: With the increasing AI involvement in medical care, the patients' WTA decreases
- H2: The higher the degree of AI involvement in medical care, the higher the intergroup anxiety patients would feel, which leads to their lower WTA AI medical care
- H3: The higher the degree of AI involvement in medical care, the higher the realistic individual threats patients would feel, which leads to their lower WTA AI medical care
- H4: The higher the degree of AI involvement in medical care, the higher the symbolic individual threats patients would feel, which leads to their lower WTA AI medical care
- H5: The higher the degree of AI involvement in medical care, the higher the realistic group threats patients would feel, which leads to their lower WTA AI medical care
- H6: The higher the degree of involvement in medical care, the higher the symbolic group threats patients would feel, which leads to their lower WTA AI medical care

[Open in a separate window](#)

Study Design and Participants 2.3.1

The authors tested all hypotheses in two separate experiments. We recruited participants for two experiments through the online professional research platform Credamo.¹ All participants were provided with electronic informed consent before participating in the experiment. We promise participants that the experiment survey results will only be used for academic research purposes but not for any commercial purposes, and that the answers involving personal information will be strictly confidential. Participants who agreed continued the experiment, whereas those who refused were allowed to drop out. The experiment collected demographic data of participants, which include age and gender, and personal information, which includes answering duration, IP address, longitude, latitude, province, and city, to ensure the authenticity and validity of the results. Participants in the two experiments were randomly assigned to the between-subjects design to make the groups comparable.

With the most commercially successful precision surgical robots (such as Da Vinci surgical robot) as the background, the experiment 1 explored the influence of AI involvement on patients' WTA treatment (H1) in high-involvement condition (AI-autonomous treatment), medium-involvement condition (AI-assisted treatment), and low-involvement condition (a human doctor) and examined that the potential cause of patients' resistance to AI health care is intergroup anxiety (H2).

In experiment 1, 446 subjects (median age = 30.4, 65.2% women) were recruited to complete the experiment in exchange for monetary compensation. Participants were randomly assigned into three manipulation conditions and read different descriptions of surgical treatment options relatively ([Longoni et al., 2019](#)). Participants in the high-involvement condition read that "surgical scheme will be evaluated by an intelligent program. Using algorithms for comparison. Using minimally invasive stereotactic high-precision surgical robots." Participants in the mid-involvement condition read that "surgical scheme will be evaluated by surgical specialists with the help of intelligent medical evaluation. Based on clinical experience. Operating highly accurate surgical robot." Participants in the low-involvement condition read that "the surgical scheme are evaluated by surgical specialists. Based on clinical experience. Cooperating with professional medical team to perform surgery." All participants were told that surgical robots were as accurate as surgical specialists.

To avoid the particularity of surgical treatment scenarios, in experiment 2, we verified the influence of AI involvement on patients' WTA in the diagnostic scenario (H1). The mediating effects of realistic individual threats (H3), symbolic individual threats (H4), realistic group threats (H5), and symbolic group threats (H6) were further discussed. The research background of experiment 2 comes from the current genetic testing project based on AI deep learning algorithm which can carry out diagnostic screening that includes genetic diseases, cancer risk, genetic defects, etc. ([Longoni et al., 2019](#)).

A total of 330 subjects (median age = 29.2, 64% women) participated in experiment 2 and received monetary compensation. Participants were randomly assigned to read descriptions of two diagnostic screening scenarios with varying degrees of AI involvement (AI-autonomous diagnosis vs. AI-assisted diagnosis). Participants in the AI-autonomous diagnostic condition were highlighted with "analysis based on genetic big data analysis and deep learning algorithms, and assessment reports and detailed health management recommendations generated entirely by advanced AI analysis techniques." Participants in AI-assisted diagnostic conditions were

emphasized that “a professional doctor will evaluate your genetic report and make recommendations based on intelligent test results.”

Measures 2.3.2

Intergroup Anxiety

The measurement of intergroup anxiety was a modified version of the intergroup anxiety scale developed by [Stephan and Stephan \(1985\)](#). In the previous studies, researchers have used this measurement to examine how people feel when interacting with members of other races ([Stephan et al., 2002](#); [Tausch et al., 2007](#)). In this study, participants read the following sentence: “I have the following emotions when I think about conducting a surgery by a highly accurate surgical robot/by a surgical specialist with the help of intelligent medical devices/by surgical specialist:” Participants rated how nervous, worried, and afraid they felt using 5-point Likert-type scales (1 = not at all, 5 = very). These items produced a reliable intergroup anxiety index (Cronbach’s $\alpha = 0.90$).

Realistic Individual Threats

As mentioned above, realistic individual threats include threats to an individual’s rights and welfare. Therefore, we used privacy concerns to measure realistic individual threats. The measurement was used in the study of the impact of electronic medical records on patients’ willingness to share personal health data ([Cherif et al., 2021](#)). Scale items include “using this medical method would collect too much personal information about me,” “using this medical method would cause my personal data to be disclosed,” “sharing my personal information with other health care providers without my authorization,” and “using my personal data for other purposes without my authorization” ([Kim et al., 2008](#); [Ponte et al., 2015](#)). Responses were made on 5-point Likert-type scales ranging from (1) strongly disagree to (5) strongly agree (Cronbach’s $\alpha = 0.92$).

Symbolic Individual Threats

The autonomy of machines has been shown to pose a threat to individual identity and uniqueness ([Złotowski et al., 2017](#)). We adopt the uniqueness neglect ([Longoni et al., 2019](#)) as a measure of symbolic individual threats. Uniqueness neglect was originally adapted from the personal sense of uniqueness scale ([Şimşek and Yalınçetin, 2010](#)). Participants indicated to what extent they agreed with the following statements “the uniqueness of my health condition cannot be recognized,” “my personal special condition will not be considered,” and “no treatment plan can be made based on my special condition” (Cronbach’s $\alpha = 0.83$). The response format consisted of a 5-point Likert-type scale ranging from strongly disagree to strongly agree.

Realistic Group Threats

The measurement method of realistic group threats is adapted from the definition of realistic group threats ([Stephan et al., 2002](#)), and the description focuses on the threat of external groups to employment resources and economic resources. This measure has been used by many researchers to examine the realistic threats posed by immigrants and ethnic minorities ([Stephan et al., 2002](#); [Tausch et al., 2007](#)). A number of three items were used for the measurement in this study, which include “AI medical care replaced the original job opportunities of doctors,” “AI medical care will lead to a higher unemployment of health care workers,” and

“AI medical care will make it more difficult for medical graduates to find jobs” (Cronbach’s $\alpha = 0.82$). Participants were also rated on a 5-point Likert-type scale, with a higher score indicating a greater perceived threat.

Symbolic Group Threats

The measurement of symbolic group threats also refers to the definition of symbolic group threats ([Stephan et al., 2002](#)), which focuses on value system and belief. We used a single item “AI medical care will threaten the health care system of our country” for participants to evaluate (1 = strongly disagree, 5 = strongly agree).

Willingness to Accept

The measurement of WTA used the methods in the study of understanding, explaining, and utilizing medical AI ([Cherif et al., 2021](#)). In experiment 1, participants were asked “How likely would you choose to perform a surgical procedure with a highly accurate surgical robot/surgical specialist using intelligent medical equipment/surgical specialist?” and rated the question on a 5-point Likert-type scale (1 = not at all likely, 5 = very likely). In experiment 2, participants were asked “how likely they are to choose to have health advice provided entirely by AI analytics/human experts with the help of intelligent testing results,” with a score of 1–5 (1 = not at all likely, 5 = very likely).

Data Analysis 2.3.3

Main Effect

In both experiments 1 and 2, one-way ANOVA was used to verify the impact of the degree of AI involvement in medical care on patients’ WTA. The independent variable, the degree of AI involvement, is a categorical variable, which was transformed to a dummy variable at the first.

Mediation Effect

To verify the mediating role of intergroup anxiety in the relationship between the degree of AI involvement and patient WTA(H2). We use SPSS (PROCESS Procedure for SPSS version 3.3 is written by [Hayes, 2013](#)) to test the mediating effect of multiple categories of independent variables based on the bootstrap ([Hayes, 2013](#)).

To verify realistic individual threats (H3), symbolic individual threats (H4), realistic group threats (H5), and symbolic group threats (H6) which mediate the relationship between degree of AI involvement and patient’s WTA, we use SPSS PROCESS Model 4 to conduct a multiple parallel mediation effect test by bootstrap method ([Preacher and Hayes, 2004](#)).

Results

The Impact of Artificial Intelligence Involvement on Patients' Willingness to Accept in the Treatment Scenario

Under the same surgical precision, patients have the highest WTA surgical experts ($M_{low} = 4.47$, $SD = 0.66$), followed by AI as an auxiliary tool ($M_{mid} = 3.85$, $SD = 0.89$). Patients had the lowest WTA fully autonomous AI health care [$M_{high} = 3.40$, $SD = 1.08$, $F(2,42) = 53.00$, $p < 0.001$, refer to Table 2].

TABLE 2

The impact of the AI involvement on patients' WTA in the treatment scenario ($n = 446$).

	<i>N</i>	<i>M</i>	<i>SD</i>	<i>SE</i>	95% CI		Min	Max
					Lower	Upper		
Low involvement	148	4.47	0.664	0.055	4.36	4.57	2	5
Mid involvement	150	3.85	0.893	0.073	3.71	4.00	2	5
High involvement	148	3.40	1.080	0.089	3.22	3.57	1	5
Total	446	3.91	0.994	0.047	3.81	4.00	1	5

The Mediating Role of Intergroup Anxiety

The omnibus test of total effect of AI involvement on patients' WTA: $F(2,443) = 53.00$ ($p < 0.001$) indicates that the two relative total effects are not all 0. The omnibus test of direct effect of AI involvement on patients' WTA: $F(2,442) = 40.23$ ($p < 0.001$) indicates that the two relative direct effects are not all 0. Therefore, it is necessary to conduct further relative mediation analysis.

The results of the relative mediation analysis were as follows: with the low involvement as the reference level, the bootstrap confidence interval of 95% of mid involvement was $[-0.167, -0.095]$, excluding 0, which indicates significant relative mediating effect ($a_1 = 0.293$, $b = -0.285$, $a_1b = -0.083$). That is, patients' intergroup anxiety about AI-assisted medical care was 0.293 higher than that of human surgical experts ($a_1 = 0.293$). Therefore, the WTA AI-assisted medical care also decreased by 0.530 ($c_1' = -0.530$, $p < 0.001$). The relative total effect was significant ($c_1 = -0.613$, $p < 0.001$), and the relative mediating effect was 13.6% ($-0.083/-0.613$).

As above, with low involvement as the reference level, the 95% bootstrap confidence interval of high involvement was $[-0.285, -0.100]$, excluding 0, which indicates significant relative mediating effect ($a_2 = 0.649$, $b = -0.285$, $a_2b = -0.185$). In other words, patients' intergroup anxiety about fully autonomous AI medical was 0.649 higher than that of human surgical experts ($a_2 = 0.649$), so the WTA fully autonomous AI medical was also reduced by 0.88 ($c_2' = -0.883$, $p < 0.001$). The relative total effect was significant ($c_2 = -1.068$, $p < 0.001$), and the relative mediating effect was 17.3% ($-0.185/-1.068$). The results are shown in [Figure 2](#) and [Table 3](#).

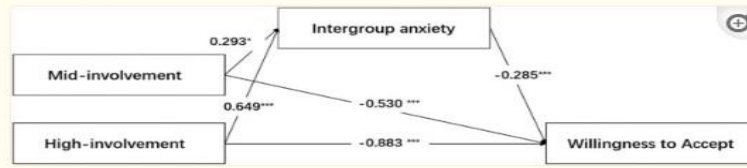


FIGURE 2

The result of experiment 2. * $p < 0.05$, *** $p < 0.001$.

TABLE 3

The mediating role of intergroup anxiety ($n = 330$).

Model pathways	Coefficient	Standardized estimate	p	95% CI		Ratio of effect
				Lower	Upper	
Intergroup anxiety on						
Mid involvement (a1)	0.293	0.136	0.032	0.026	0.559	
High involvement (a2)	0.649	0.136	<0.001	0.381	0.916	
Willingness to Accept on						
Intergroup anxiety (b)	-0.285	0.034	<0.001	-0.351	-0.219	
Relative total effects						
Mid involvement (c1)	-0.613	0.104	< 0.001	-0.817	-0.409	
High involvement (c2)	-1.068	0.104	< 0.001	-1.373	-0.863	
Relative direct effects						
Mid involvement (c1')	-0.530	0.097	< 0.001	-0.720	-0.339	
High involvement (c2')	-0.883	0.099	< 0.001	-0.001	-0.688	
Relative indirect effects						
Mid involvement (a1*b)	-0.083	0.040		-0.167	-0.010	13.6%
High involvement (a2*b)	-0.185	0.047		-0.286	-0.100	17.3%

The Impact of Artificial Intelligence Involvement on Patients' Willingness to Accept in the Diagnostic Scenario

The willingness of patients to accept evaluation reports issued by human experts ($M_{\text{low}} = 4.05$, $SD = 0.66$) is higher than that of big data analysis and deep learning algorithm [$M_{\text{high}} = 3.63$, $SD = 0.98$, $F(1, 15) = 21.07$, $p < 0.001$, refer to [Table 4](#)].

TABLE 4

The impact of the AI involvement on patients' WTA in the diagnostic scenario ($n = 330$).

	N	M	SD	SE	95% CI		Min	Max
					Lower	Upper		
Low involvement	164	4.05	0.658	0.051	3.95	4.16	2	5
High involvement	166	3.63	0.980	0.076	3.48	3.78	1	5
Total	330	3.84	0.861	0.047	3.75	3.94	1	5

The Mediating Role of Realistic Individual Threats, Symbolic Individual Threats, Realistic Group Threats, Symbolic Group Threats

The results of the mediation test showed that the 95% confidence interval (LLCI = -0.220, ULCI = -0.062) of the indirect effect of privacy concern representing realistic individual threats did not contain 0, which indicates the existence of the mediation effect. The 95% confidence interval of the direct effect (LLCI = -0.358, ULCI = -0.039) did not contain 0, which indicates that privacy concern was an incomplete mediator and the mediating effect was -0.132. Similarly, uniqueness neglect that represents symbolic individual threats was as an incomplete mediator (LLCI = -0.137, ULCI = -0.003), with a mediating effect of -0.061. Realistic group threats were incomplete mediation (LLCI = -0.091, ULCI = -0.004), and the mediation effect was -0.040. However, the confidence interval of the indirect effect of symbolic group threats (LLCI = -0.094, ULCI = 0.034) contained 0, which indicates that the mediating effect did not exist. The result is shown in [Table 5](#) and [Figure 3](#).

TABLE 5

The mediating role of realistic individual threats, symbolic individual threats, realistic group threats, and symbolic group threats ($n = 446$).

Model pathways	Standardized effect	SE	95% CI		Ratio of effect
			Lower	Upper	
Indirect effects	-0.260	0.065	-0.390	-0.137	53.0%
AI involvement → Realistic individual threats → Willingness to Accept	-0.132	0.040	-0.220	-0.062	26.9%
AI involvement → Symbolic individual threats → Willingness to Accept	-0.061	0.034	-0.137	-0.003	12.5%
AI involvement → Realistic group threats → Willingness to Accept	-0.040	0.022	-0.091	-0.004	8.1%
AI involvement → Symbolic group threats → Willingness to Accept	-0.027	0.032	-0.094	0.034	5.6%
Direct effects	-0.231	0.081	-0.358	-0.039	
Total effects	-0.491	0.092	-0.603	-0.241	

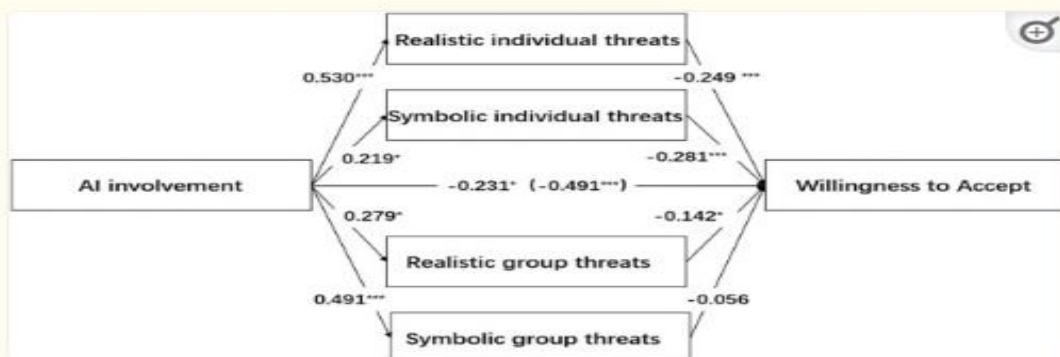


FIGURE 3

The result of experiment 2. * $p < 0.05$, *** $p < 0.001$.

Discussion

The results of this study showed that patients were reluctant to use AI for medical treatment, even though they knew that AI could provide expert-level accuracy in medical care. The willingness to choose a human doctor is higher than that of AI-assisted medical devices and far higher than that of fully autonomous intelligent medical devices. This means that while AI can provide accurate and effective services in health care, patients are still more likely to rely on human doctors.

According to ITT, people tend to anticipate threats from outside groups, which results in prejudice ([Stephan et al., 2005](#); [Morrison et al., 2009](#); [Myers et al., 2013](#)). The study result preliminarily confirmed that people will have intergroup threats when facing AI and resist using AI for medical treatment because of intergroup anxiety. We can see that although the application of AI technology has been all over the medical industry, patients still have a bias against AI medical care.

One of the reasons for this bias and resistance is from realistic individual threats; that is, patients worry about whether there is a privacy leakage and other issues that would harm their rights. Another reason is symbolic individual threats, which means patients generally worry about whether they can receive precise medicine tailored to their condition when using AI medical care. There is also another reason for symbolic group threats related to the wellbeing of healthcare workers. However, symbolic group threats failed to pass the mediation effect verification. From the results, the higher the degree of AI intervention, the more likely patients would perceive the threat to the existing medical system. Although patients have realized that this will have a transformative impact on the healthcare system, there is no significant difference in consumers' WTA AI as it has been widely used in various healthcare scenarios.

The previous studies have confirmed that people can perceive threats from AI technology in human–computer interaction scenarios. When faced with autonomous AI technology, people experience loss of situational control ([Stein et al., 2019](#)), undermining uniqueness of human identity ([Złotowski et al., 2017](#); [Stein et al., 2019](#)), feeling security risks ([Złotowski et al., 2017](#)), and feeling resource competition ([Złotowski et al., 2017](#)), etc.

From the perspective of theoretical contribution, this study explores where patients' concerns about AI health care come from (which includes individual level, group level, realistic level, and symbolic level) an integrated framework based on ITT. In addition, a test of multiple parallel mediating effects was used to observe the overall mediating effect of all perceived threats and observe the effect of a single threat after eliminating other

mediators. Meanwhile, the relative degree of the impact of threats from different levels on patients' willingness to use AI medical services was also compared.

From the perspective of practical contribution, the research results revealed that patients would have greater realistic individual threats when facing AI health care, such as personal privacy disclosure. The second was symbolic individual threats, such as the lack of precision medical services tailored to the individual's uniqueness. The least affected were perceived realistic group threats, such as threats to the employment of healthcare workers. When emphasizing the intelligence, accuracy, and cost-effectiveness of AI health care, relevant departments and enterprises may have neglected to understand the sources of negative attitudes and irrational fears about AI health care from the perspective of patients. The research conclusions can help government departments, institutions, and enterprises formulate targeted policies, strategies, or product plans, eliminating patients' doubts, improving the application of AI in the medical industry, and promoting the benign development of AI health care.

This study has the following limitations. First of all, many other perceived threats can lead to negative attitudes or avoidance behaviors of patients toward AI health care. In this study, only a few representative variables were selected according to the ITT theory to measure threats from different levels. Second, only a single item was used to measure symbolic group threats. These problems need to be further explored by developing more comprehensive scales in the future studies. Third, the research was only conducted in China, so whether there are significant differences in research results under different social cultures needs to be further explored.

Despite these limitations, our research reveals the psychological mechanism of patients' resistance to the use of AI health care, which deepens the understanding of the current AI medical application. The research conclusions can provide guidance for the application and development of AI in the medical field and provide a reference for policy-making of relevant departments and product promotion of relevant enterprises.

Conclusion

The study suggests that patients experience intergroup anxiety in the face of AI health care and will resist using AI health care because of the perceived threat. Threats from different levels have a different extent of impacts on patients. In healthcare scenarios, patients first pay attention to threats related to themselves at the individual level, such as personal safety and personal rights. Moreover, patients are more affected by realistic threats (such as personal privacy disclosure) than symbolic threats (such as ignoring individual uniqueness). In contrast, group-level threats have less impact on patients.

References list

Chapter One:

1. Science Fiction and Philosophy: From Time Travel to Superintelligence.
2. Artificial Intelligence: A Guide for Thinking Humans
3. Adams, S., Arel, I., Bach, J., Coop, R., Furlan, R., Goertzel, B., & Sowa, J. F. (2012). Mapping the landscape of human-level artificial general intelligence. *AI Magazine*, 33, 25–42.
4. Goertzel, B. (2014a). GOLEM: towards an AGI meta-architecture enabling both goal preservation and radical self-improvement. *Journal of Experimental & Theoretical Artificial Intelligence*, 26, 391–403.
5. Kornai, A. (2014). Bounding the impact of AGI. *Journal of Experimental & Theoretical Artificial Intelligence*, 26, 417–438.
6. Yudkowsky, E. (2008). Artificial intelligence as a positive and negative factor in global risk. *Global catastrophic risks*, 1(303), 184.

Chapter Two:

1. Agarwal R., Dugas M., Gao G. G., Kannan P. (2020). Emerging technologies and analytics for a new era of value-centered marketing in healthcare. *J. Acad. Mark. Sci.* 48 9–23. 10.1007/s11747-019-00692-4 [CrossRef] [Google Scholar]
2. Alexander R. D. (1974). The evolution of social behavior. *Annu. Rev. Ecol. Systemat.* 5 325–383. [Google Scholar]
3. Baumeister R. F. (2010). *The Self*. Oxford: Oxford university press. [Google Scholar]
4. Cherif E., Bezaz N., Mzoughi M. (2021). Do personal health concerns and trust in healthcare providers mitigate privacy concerns? Effects on patients’ intention to share personal health data on electronic health records. *. Social Sci. Med.* 283:114146. 10.1016/j.socscimed.2021.114146 [PubMed] [CrossRef] [Google Scholar]
5. Dunbar R. I. M. (2013). *Primate Social Systems*. Cham: Springer Science & Business Media. [Google Scholar]
6. Eastwood J., Snook B., Luther K. (2012). What people want from their professionals: attitudes toward decision-making strategies. *J. Behav. Decis. Mak.* 25 458–468. 10.1002/bdm.741 [CrossRef] [Google Scholar]
7. Feshki M. G., Shijani O. S. (2016). “Improving the heart disease diagnosis by evolutionary algorithm of PSO and Feed Forward Neural Network,” in *Proceedings of the 2016 Artificial Intelligence and Robotics (IRANOPEN)* (Qazvin: IEEE;) [Google Scholar]
8. Granulo A., Fuchs C., Puntoni S. (2019). Psychological reactions to human versus robotic job replacement. *Nat. Hum. Behav.* 3 1062–1069. 10.1038/s41562-019-0670-y [PubMed] [CrossRef] [Google Scholar]
9. Grove W. M., Zald D. H., Lebow B. S., Snitz B. E., Nelson C. (2000). Clinical versus mechanical

- prediction: a meta-analysis. *Psychol. Assess.* 12:19. 10.1037/1040-3590.12.1.19 [PubMed] [CrossRef] [Google Scholar]
10. Haslam N., Loughnan S., Kashima Y., Bain P. (2008). Attributing and denying humanness to others. *Eur. Rev. Soc. Psychol.* 19 55–85. 10.1080/10463280801981645 [CrossRef] [Google Scholar]
 11. Hayes A. F. (2013). *Introduction to Mediation, Moderation, and Conditional Process Analysis: a Regression-based Approach*. New York, NY: Guilford Press. [Google Scholar]
 12. Hazarika I. (2020). Artificial intelligence: opportunities and implications for the health workforce. *Int. Health* 12 241–245. 10.1093/inthealth/ihaa007 [PMC free article] [PubMed] [CrossRef] [Google Scholar]
 13. Kaplan F. (2004). Who is afraid of the humanoid? Investigating cultural differences in the acceptance of robots. *Int. J. Human. Robot.* 1 465–480. 10.1142/s0219843604000289 [CrossRef] [Google Scholar]
 14. Kettle K. L., Häubl G. (2011). The signature effect: signing influences consumption-related behavior by priming self-identity. *J. Consum. Res.* 38 474–489. 10.1086/659753 [CrossRef] [Google Scholar]
 15. Kim D. J., Ferrin D. L., Rao H. R. (2008). A trust-based consumer decision-making model in electronic commerce: the role of trust, perceived risk, and their antecedents. *Decis. Support Syst.* 44 544–564. 10.1016/j.dss.2007.07.001 [CrossRef] [Google Scholar]
 16. Longoni C., Bonezzi A., Morewedge C. K. (2019). Resistance to medical artificial intelligence. *J. Consum. Res.* 46 629–650. [Google Scholar]
 17. Mei X., Lee H.-C., Diao K.-Y., Huang M., Lin B., Liu C., et al. (2020). Artificial intelligence-enabled rapid diagnosis of patients with COVID-19. *Nat. Med.* 26 1224–1228. [PMC free article] [PubMed] [Google Scholar]
 18. Morrison K. R., Fast N. J., Ybarra O. (2009). Group status, perceptions of threat, and support for social inequality. *J. Exp. Soc. Psychol.* 45 204–210. 10.1016/j.jesp.2008.09.004 [CrossRef] [Google Scholar]
 19. Myers C., Abrams D., Rosenthal H. E., Christian J. (2013). Threat, prejudice and stereotyping in the context of Japanese, North Korean, and South Korean intergroup relations. *Curr. Res. Soc. Psychol.* 20 76–85. [Google Scholar]
 20. Nov O., Aphinyanaphongs Y., Lui Y. W., Mann D., Porfiri M., Riedl M., et al. (2020). The transformation of patient-clinician relationships with ai-based medical advice: a “bring your own algorithm” Era in Healthcare. *arXiv [Preprint]* Available online at: 10.48550/arXiv.2008.05855 [accessed on August 13, 2020]. [CrossRef] [Google Scholar]
 21. Ponte E. B., Carvajal-Trujillo E., Escobar-Rodríguez T. (2015). Influence of trust and perceived value on the intention to purchase travel online: integrating the effects of assurance on trust antecedents. *Tour. Manage.* 47 286–302. 10.1016/j.tourman.2014.10.009 [CrossRef] [Google Scholar]
 22. Preacher K. J., Hayes A. F. (2004). SPSS and SAS procedures for estimating indirect effects in simple mediation models. *Behav. Res. Methods Instr. Comput.* 36 717–731. 10.3758/bf03206553 [PubMed] [CrossRef] [Google Scholar]

23. Promberger M., Baron J. (2006). Do patients trust computers? *J. Behav. Decis. Mak.* 19 455–468. 10.1002/bdm.542 [CrossRef] [Google Scholar]
24. Şimşek ÖF., Yalınçetin B. (2010). I feel unique, therefore I am: the development and preliminary validation of the personal sense of uniqueness (PSU) scale. *Pers. Individ. Differ.* 49 576–581. 10.1016/j.paid.2010.05.006 [CrossRef] [Google Scholar]
25. Stein J.-P., Liebold B., Ohler P. (2019). Stay back, clever thing! Linking situational control and human uniqueness concerns to the aversion against autonomous technology. *Comput. Hum. Behav.* 95 73–82. 10.1016/j.chb.2019.01.021 [CrossRef] [Google Scholar]
26. Stephan W. G., Boniecki K. A., Ybarra O., Bettencourt A., Ervin K. S., Jackson L. A., et al. (2002). The role of threats in the racial attitudes of Blacks and Whites. *Pers. Soc. Psychol. Bull.* 28 1242–1254. 10.1177/01461672022812009 [CrossRef] [Google Scholar]
27. Stephan W. G., Renfro C., Davis M. D. (2008). “The role of threat in intergroup relations,” in *Improving intergroup relations: Building on the legacy of Thomas*, eds Pettigrew F., Wagner U., Tropp L. R., Finchilescu G., Tredoux C. (Hoboken, NJ: Blackwell Publishing;), 55–72 [Google Scholar]
28. Stephan W. G., Renfro C. L., Esses V. M., Stephan C. W., Martin T. (2005). The effects of feeling threatened on attitudes toward immigrants. *Int. J. Intercult. Relat.* 29 1–19. 10.1186/s12913-016-1423-5 [PMC free article] [PubMed] [CrossRef] [Google Scholar]
29. Stephan W. G., Stephan C. W. (1985). Intergroup anxiety. *J. Soc. Issues* 41 157–175. [Google Scholar]
30. Stephan W. G., Stephan C. W. (2000). “An integrated threat theory of prejudice,” in *Reducing Prejudice and Discrimination*, ed. Oskamp S. (Mahwah, NJ: Lawrence Erlbaum Associates Publishers;), 23–45. [Google Scholar]
31. Stephan W. G., Ybarra O., Morrison K. R. (2009). “Intergroup threat theory,” in *Handbook of Prejudice, Stereotyping, and Discrimination* ed. Nelson T. D. (Hove: Psychology Press;), 43–59. [Google Scholar]
32. Stephan W. G., Ybarra O., Rios K. (2015). “Intergroup threat theory,” in *Handbook of Prejudice, Stereotyping, and Discrimination*, ed. Nelson T. D. (Hove: Psychology Press;), 255–278. [Google Scholar]
33. Tajfel H. (1974). Social identity and intergroup behaviour. *Soc. Sci. Inform.* 13 65–93. 10.1177/053901847401300204 [CrossRef] [Google Scholar]
34. Takiddin A., Schneider J., Yang Y., Abd-Alrazaq A., Househ M. (2021). Artificial Intelligence for Skin Cancer Detection: scoping review. *J. Med. Internet Res.* 23:e22934. 10.2196/22934 [PMC free article] [PubMed] [CrossRef] [Google Scholar]
35. Tausch N., Tam T., Hewstone M., Kenworthy J., Cairns E. (2007). Individual-level and group-level mediators of contact effects in Northern Ireland: the moderating role of social identification. *Br. J. Soc. Psychol.* 46 541–556. 10.1348/014466606X155150 [PubMed] [CrossRef] [Google Scholar]
36. Trope Y. (1975). Seeking information about one’s ability as a determinant of choice among tasks. *J.*

Pers. Soc. Psychol. 32:1004. 10.1037/0022-3514.32.6.1004 [CrossRef] [Google Scholar]

37. Yamashita R., Bird K., Cheung P. Y.-C., Decker J. H., Flory M. N., Goff D., et al. (2021). Automated identification and measurement extraction of pancreatic cystic lesions from free-text radiology reports using natural language processing. *Radiology* 4:e210092. [PMC free article] [PubMed] [Google Scholar]
38. Złotowski J., Yogeeswaran K., Bartneck C. (2017). Can we control it? Autonomous robots threaten human identity, uniqueness, safety, and resources. *Int. J. Hum. Comput. Stud.* 100 48–54. 10.1016/j.ijhcs.2016.12.008 [CrossRef] [Google Scholar].

Table of shapes

Figure number	Figure title	Page number
FIGURE 1	The research model of experiment (A) and (B)	19
FIGURE 2	The result of experiment 2. *p < 0.05, ***p < 0.001.	24
FIGURE 3	The result of experiment 2. *p < 0.05, ***p < 0.001.	25

TABLE number	TABLE title	TABLE number
TABLE 1	The hypotheses.	19
TABLE 2	The impact of the AI involvement on patients' WTA in the treatment scenario (n = 446).	23
TABLE 3	The mediating role of intergroup anxiety (n = 330).	24
TABLE 4	The impact of the AI involvement on patients' WTA in the diagnostic scenario (n = 330).	24
TABLE 5	The mediating role of realistic individual threats, symbolic individual threats, realistic group threats, and symbolic group threats (n = 446).	25

Appendices Chapter

Appendices

Kind regards

I am honored to place in your hands this questionnaire prepared for the purposes of scientific research with the aim of completing a thesis entitled “The impact of artificial intelligence on human resources specializations in departments.”

And the government sector in the Kingdom of Saudi Arabia,” as artificial intelligence has kept pace with many of the tasks and workers that we perform on a daily basis.

For this reason, we ask you to answer the questions included in the form so that we can complete this scientific research.

Personal questions:

1. *Demographic information:*

- how old are you?
- What's your gender?
- What is your education level?
- What is your field of work?
- What country do you reside in?

2. *Awareness of artificial intelligence:*

- Have you ever heard of artificial intelligence?
- From what sources do you get your information about artificial intelligence? (TV, Internet, work, friends, etc.)

3. *Personal experiences:*

- Have you ever used artificial intelligence?
- If yes, where have you used artificial intelligence?

4. *Perceptions and trends:*

- How much do you think about artificial intelligence?
- Do you recommend working with artificial intelligence?

Variable Dimensions	Number Of Statements	Source
First dimension: The reality of using artificial intelligence in human resources management In the government sector in the Kingdom of Saudi Arabia	4	Habeeb, A. (2017). Artificial intelligence Ahmed University of Mansoura
Second dimension: The contribution of artificial intelligence to human resources management in the government sector in the Kingdom of Saudi Arabia	5	
Third dimension: Difficulties facing artificial intelligence in human resources management in the government sector in the Kingdom of Saudi Arabia	3	

The first question states" The reality of using artificial intelligence in human resources management in the government sector in the Kingdom of Saudi Arabia"?

Number	Questionnaire statements	Degree of approval			
		disagree	neutral	Agree	Strongly agree
1	Attendance and departure for government sector employees are signed using artificial intelligence.				
2	Artificial intelligence reduces the tasks assigned to human resources officials and eliminates the routine manual tasks that take up most of their working hours.				
3	Artificial intelligence helps exploit,Time wasted on more productive tasks Such as motivating employees and enriching the cultural sense And their creativity.				
4	There is an electronic platform for the employee to request, Leave, assignment and resource work, Humanity				

The Second question states" The contribution of artificial intelligence to human resources management in the government sector in the Kingdom of Saudi Arabia "?

Number	Questionnaire statements	Degree of approval			
		disagree	neutral	Agree	Strongly agree
1	The number of employees in the government sector has clearly decreased after the introduction of artificial intelligence				
2	The use of artificial intelligence in the government sector reduces the number of employees				
3	The use of artificial intelligence in the Ministry reduced customer visits to implement their services through the relevant government sector employees.				
4	There are a lot of changes in the tasks staff functions after the introduction of intelligence artificial work environment				
5	Artificial intelligence helps employees improve work efficiency.				

The Third question states" Difficulties facing artificial intelligence in human resources management in the government sector in the Kingdom of Saudi Arabia"?

Number	Questionnaire statements	Degree of approval			
		disagree	neutral	Agree	Strongly agree
1	Public opinion and even academic circles fear an uncertain future regarding the fate of humans in tomorrow's machine world				
2	Difficulty in technological follow-up on the one hand, huge and distant financing the investment is not clear.				
3	The government sector needs experts in the field of artificial intelligence in order to monitor electronic customer services.				

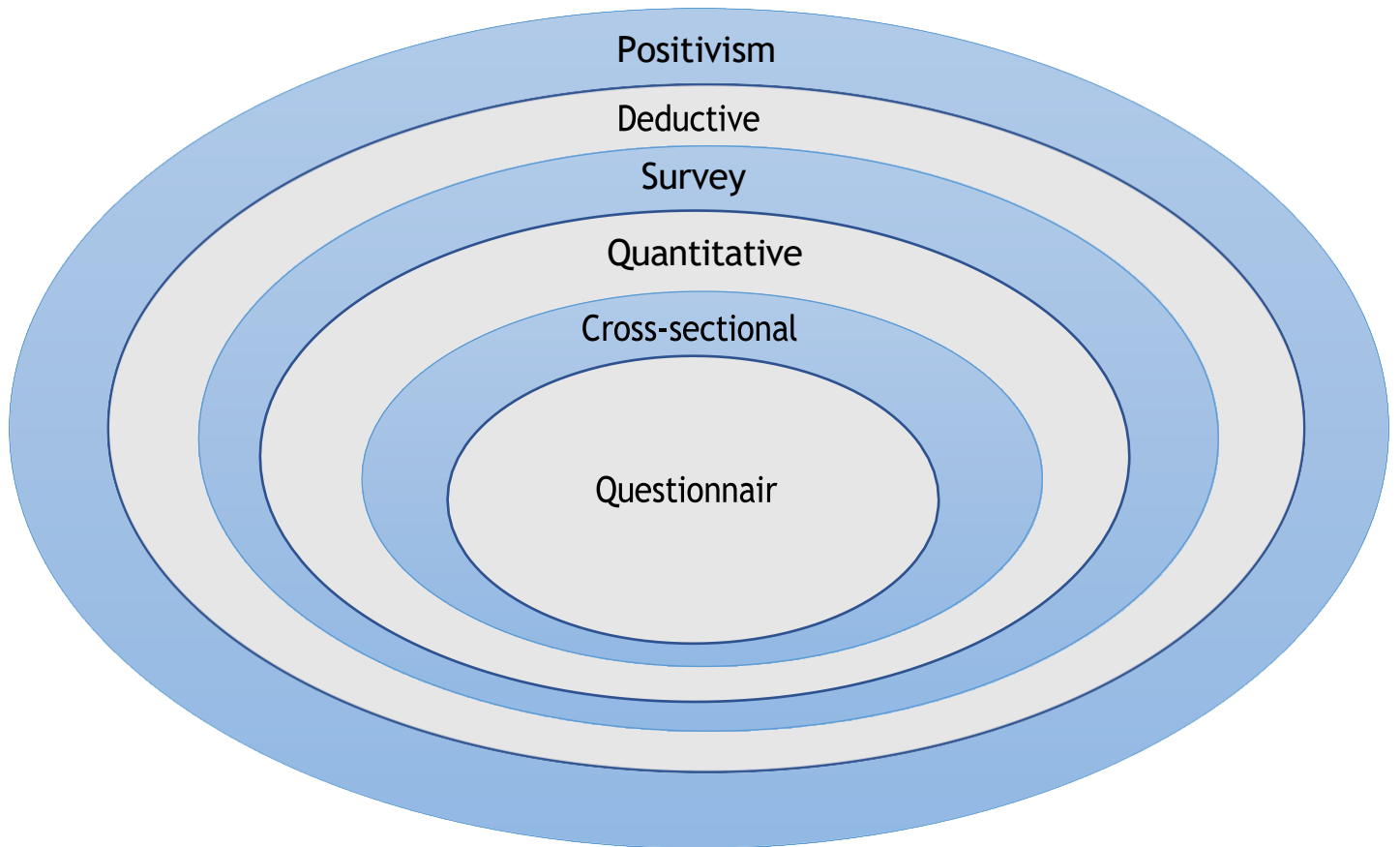
3. Chapter 3: Research Methodology

This chapter outlines the research methodology employed to investigate “The impact of artificial intelligence on human resources specializations in departments”. It details the operational definitions for research variables, research design, research population & sampling methods and technique, data collection methods, types of data, and data analysis methods & procedures.

3.1.2:Operational definitions for research variables:

The descriptive analytical approach was used, as the theoretical approach was used by referring to theoretical literature and studies related to the subject; to form a theory about the specialized ideas and concepts in the field of study, and to review the studies. Previous relevant literature, through analysis of the study’s literature; to reach an answer to the study’s questions and provide a number of recommendations.

3.3: Research design



3.4 Research population & Sampling methods and technique

3.4.1:Research population:

The research community consisted of all employees of departments in the government sector in the Kingdom of Saudi Arabia.

3.4.2:Research sample:

The research sample consisted of one-third of the original community, numbering (50) male and female employees in departments in the government sector in the Kingdom of Saudi Arabia.

3.4.3:Sampling methods and technique:

The questionnaire was used as a tool to collect the necessary information about the research, as it is suitable for achieving the research objectives and answering its questions.

3.5: Data collection method:

A questionnaire was prepared based on a review of the relevant literature and previous studies in this field. In light of this, the questionnaire was formulated and written to include (3) dimensions, which contains (14) paragraphs, and the research tool in its initial form consisted of (3) dimensions. Each dimension included a number of paragraphs as shown, which are as follows:

3.5.1:The first dimension(Independent variable):

Addressing the reality of using artificial intelligence in human resources management in the government sector in the Kingdom of Saudi Arabia, and it consists of (4) paragraphs.

3.5.2:The second dimension(Dependent variable):

Addressing the contribution of artificial intelligence to human resources management in the government sector in the Kingdom of Saudi Arabia. It consists of (5) paragraphs.

3.5.3:The third dimension (Dependent variable):

Addressing the difficulties facing artificial intelligence in human resources management in the government sector in the Kingdom of Saudi Arabia, and it consists of (5) paragraphs.

The closed form was adopted in preparing the dimensions of the questionnaire, which determines the possible responses for each statement. The Likert method with a four-point scale was used, so that the answer (strongly agree) was given four points. While the answer (agree) was given three points, the answer (neutral) was given two points. Finally, the answer (disagree) was given one point.

Then, the arithmetic mean of the answers of the research sample was calculated. The length of the cells of the four-point scale (lower and upper limits) used in the research dimensions was determined. Then the range was calculated ($4-1=3$), then divided by the number of cells in the scale to obtain the correct cell length. After that, this value was added to the lowest value in the scale (or the beginning of the scale, which is the correct one); in order to determine the upper limit of this cell, and thus the length of the cells became as shown in the following table:

Degree of approval	The standard
Very large	If the arithmetic mean value is (3.26-4.0)
Large	If the arithmetic mean value is (2.51-3.25)
Medium	If the arithmetic mean value is (1.76-2.50)
Weak	If the arithmetic mean value is (1.00-1.75)

3.6: Data Analysis Methods & Procedures:

After collecting data, it is essential to analyze the information gathered to draw meaningful conclusions. As, the Statistical Package for the Social Sciences (SPSS), specifically version 28, were used to analyze the collected data.

The sample profile test was conducted, via descriptive analysis, to gain insights into the characteristics of the sample population. It helps researchers understand the demographics, preferences, and other relevant information about the individuals involved in the study.

Validity and reliability tests are crucial in ensuring that the data collected is accurate and consistent. Validity tests (Exploratory factor analysis) to determine if the research instruments measure what they are intended to measure, while reliability tests (Cronbach's Alpha test) assess the consistency of results over time.

The sample profile test was conducted, via descriptive analysis, to gain insights into the characteristics of the sample population. It helps researchers understand the demographics, preferences, and other relevant information about the individuals involved in the study.

Conclusion

Integrating artificial intelligence into institutions supports and develops the system, and gives the ability to face the biggest challenges of the digital age, accelerate progress towards achieving the goals of sustainable development, benefit from the ongoing technological revolution and reach its fruits, especially in terms of innovation, creativity, leadership and a knowledge society, and enhance human capabilities and protect rights for effective cooperation between humans and machines in life in cooperation with electronic companies, to enhance their pioneering role in the field of artificial intelligence, improve and generalize artificial intelligence skills in training programs, develop the capabilities of master trainers and enable young people to develop innovative artificial intelligence applications.

4. Chapter 4: Statistical analysis of the study results

4.1: Introduction

This chapter presents the results of the field study that were statistically analyzed using the statistical programs SPSS version 29. The current chapter of statistical analysis includes descriptive statistics for the sample under study using SPSS version 29. Testing the validity and reliability of the questionnaires used to collect the required data from the current study sample. In order to test the research hypotheses and the suitability of the model, simple linear regression analysis was conducted via SPSS 29.

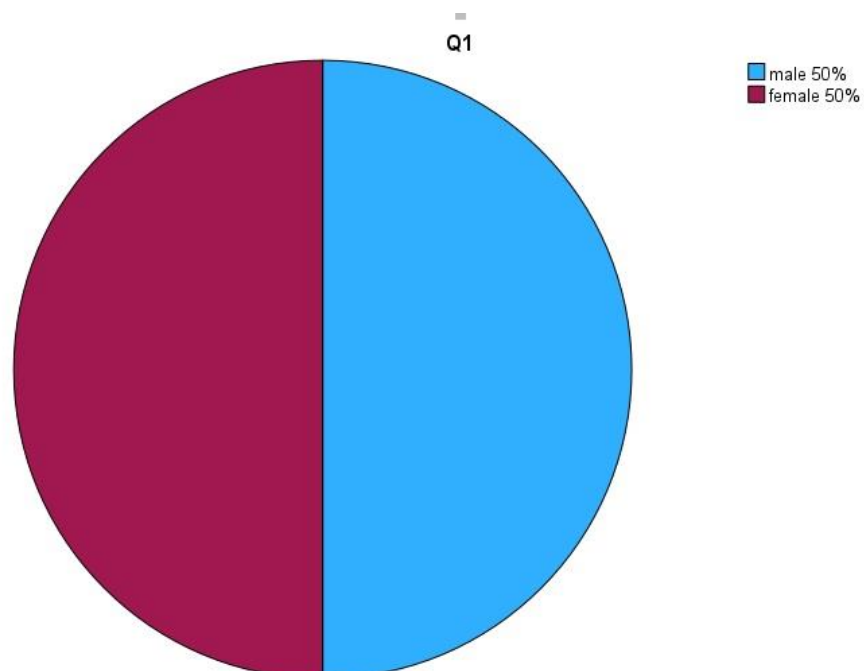
4.2 Characteristics of the study sample:

- The study sample was distributed according to gender - age group - number of years of experience - nature of work and educational level.
- Frequencies and percentages were calculated for the study sample members and are represented by demographic information that includes:
 - Gender includes (male, female).
 - The age group includes (from 25 to 45 years, Over 45 years and Under 25 years).
 - Marital status (married/ unmarried).
 - Nature of work, including (leaders/employees/technicians)
 - Educational level includes (secondary/university/postgraduate).

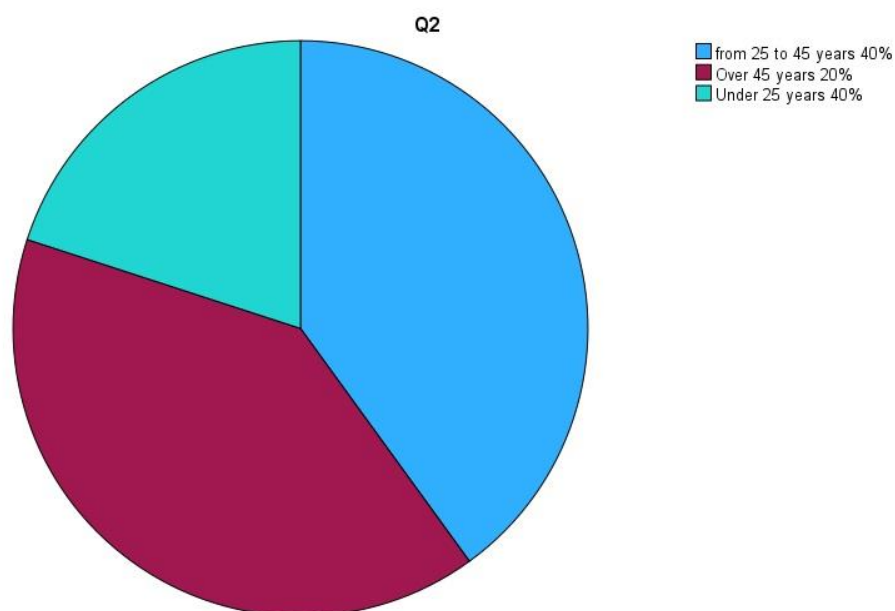
4.2.1 Description table for the study sample:

Variable	Variable classes	The number	Percentage of the total sample
Gender(Q1)	Male	5	50%
	Female	5	50%
	Total	10	100%
The age group(Q2)	Under 25 years	4	40%
	from 25 to 45 years	4	40%
	Over 45 years	2	20%
	Total	10	100%
marital status(Q3)	married	4	40%
	unmarried	6	60%
	Total	10	100%

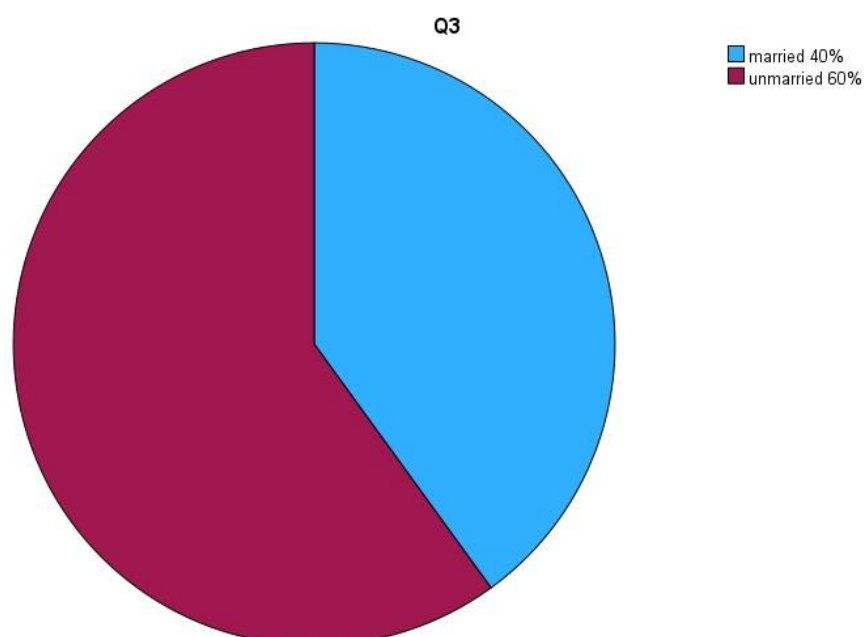
Q1					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	male	5	50.0	50.0	50.0
	female	5	50.0	50.0	100.0
	Total	10	100.0	100.0	



Q2					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	from 25 to 45 years	4	40.0	40.0	40.0
	Over 45 years	4	40.0	40.0	80.0
	Under 25 years	2	20.0	20.0	100.0
	Total	10	100.0	100.0	



Q3					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	married	4	40.0	40.0	40.0
	unmarried	6	60.0	60.0	100.0
	Total	10	100.0	100.0	



4.3 Measuring the validity and reliability of study instruments:

In order to verify the validity and reliability of the measures used in the study, the internal consistency validity of the questionnaires used to measure the study variables was tested, in addition to measuring the convergent validity by measuring the Average Variance Extracted (AVE). While the reliability of the measures used in the study was measured by Measuring the value of Cronbach's alpha, through the structural equation modeling (SEM), using the statistical analysis program SPSS version 29 .The following paragraphs and tables explain this.

4.3.1 Validity of the measures used in the study:

The internal consistency validity of the scales used to measure the study variables was tested, in addition to measuring the convergent validity by measuring the average variance extracted.

4.3.2 Internal consistency validity:

It means the extent to which each statement of the questionnaire is consistent with the variable to which it belongs. Therefore, the researcher measured the internal consistency of the questionnaires by calculating the correlation coefficients between the score of each statement and the total score of the variable to which it belongs. According to Kaiser (1974) study, a correlation coefficient of less than 0.5 is removed from the questionnaire.

4.3.3 Convergent Validity:

The average variance between statements that measure the same scale is measured by calculating the average variance extracted (AVE), whose value must be greater than 0.5 according to Hair et al (2006).The following tables show the statistical results for (correlation coefficients, standard deviation, calculated T value, and P value between the score of each statement and the total score of the variable to measure the validity of the internal consistency of the questionnaires. Also, calculating the value of the average variance extracted (AVE) to measure the convergent validity of the questionnaires through the equation model. Structural SPSS version 29, as follows:

Variable	Statements	KMO	Factor loadings	Standard deviation	P Values	Average variance extracted	
First dimension	A1	0.398	0.504	1.491	0.00	1.986	1
	A2		-0.916	1.595	0.00	1.126	
	A3		0.915	1.434	0.00	0.775	
	A4		0.937	4.650	0.00	0.113	
Second dimension	B1	0.336	0.854	1.633	0.00	2.297	1
	B2		0.871	1.494	0.00	1.494	
	B3		0.838	1.524	0.00	0.816	
	B4		-0.833	1.567	0.00	0.363	
	B5		-0.753	1.317	0.00	0.031	
Third dimension	C1	0.462	0.931	1.491	0.00	1.846	1
	C2		-0.838	1.491	0.00	0.909	
	C3		-0.527	1.370	0.00	0.245	

It is clear from the table above:

The scale of applying the first dimension: All correlation coefficients for all statements are strongly correlated with their dependent variable (the variable and its dimensions), at values greater than 0.7. In addition, the values of all correlation coefficients for the statements are statistically significant at a significance level less than 0.001. Accordingly, the internal consistency validity of the scale has been achieved. Also, from the results above related to the value of the average variance extracted AVE, it is clear that its value for the variable of applying (the variable and its dimensions) is $0.565 > 0.5$. Accordingly, the convergent validity of the questionnaire has been achieved.

The scale of applying the Second dimension: All correlation coefficients for all statements are strongly correlated with their dependent variable (the variable and its dimensions), at values greater than 0.7. In addition, the values of all correlation coefficients for the statements are statistically significant at a significance level less than 0.001. Accordingly, the internal consistency validity of the scale has been achieved. Also, from the results above related to the value of the average variance extracted AVE, it is clear that its value for the variable of applying (the variable and its dimensions) is $0.565 > 0.5$. Accordingly, the convergent validity of the questionnaire has been achieved.

The scale of applying the Third dimension: All correlation coefficients for all statements are strongly correlated with their dependent variable (the variable and its dimensions), at values greater than 0.7. In addition, the values of all correlation coefficients for the statements are statistically significant at a significance level less than 0.001. Accordingly, the internal consistency validity of the scale has been achieved. Also, from the results above related to the value of the average variance extracted AVE, it is clear that its value for the variable of applying (the variable and its dimensions) is $0.565 > 0.5$. Accordingly, the convergent validity of the questionnaire has been achieved.

4.3.2 Reliability of the study tool:

The stability of the questionnaire refers to the stability of the questionnaire results and their non-change significantly if they were redistributed to the sample individuals several times during specific time periods. To measure the stability of the questionnaires used to measure the study variables, Cronbach's alpha values were calculated using SPSS version 29. According to (2010) Hair et al, the value must be greater than 0.7 for the scale to be stable.

Variable	Number of Statements	Cronbach's alpha
First dimension	4	-1.771
Second dimension	5	0.248
Third dimension	3	-0694

(First dimension): The statistical results showed that the values of Cronbach's alpha are (-1.771), which indicates that all values are greater than 0.7. According to Hair et al (2010), the stability of the scale has been achieved.

(Second dimension): The statistical results showed that the values of Cronbach's alpha are (0.248), which indicates that all values are greater than 0.7. According to Hair et al (2010), the stability of the scale has been achieved.

(Third dimension): The statistical results showed that the values of Cronbach's alpha are (-0694), which indicates that all values are greater than 0.7. According to Hair et al (2010), the stability of the scale has been achieved.

Strongly agree	Agree	Neutral	Disagree	Strongly disagree
----------------	-------	---------	----------	-------------------

level (degree) Practice/importance	Relative weight %	Result (general trend)	The value of the arithmetic mean
very low	From 20 to less than 36%	Strongly disagree	From 1 to less than 1.80
Low	From 36 to less than 52%	Disagree	From 1.80 to less than 2.60
Middle	From 52 to less than 68%	Neutral	From 2.60 to less than 3.40
High	From 68 to less than 84%	Agree	From 3.40 to less than 4.20
very high	From 84 to less than 100%	Strongly agree	From 4.20 to less than 5

Inter-Item Correlation Matrix

	A1	A2	A3	A4	B1	B2	B3	B4	B5	C1	C2	C3
A1	1.000	-.280	.104	.271	.000	.249	.000	-.285	.396	.400	-.100	-.109
A2	-.280	1.000	-.073	-.823	-.384	.126	.087	-.387	-.222	-.187	.607	.158
A3	.104	-.073	1.000	-.258	.427	.182	.381	.223	-.235	.156	.000	-.424
A4	.271	-.823	-.258	1.000	.206	-.248	-.464	.322	.153	.000	-.542	-.270
B1	.000	-.384	.427	.206	1.000	.091	.446	.564	-.362	.000	-.046	.000
B2	.249	.126	.182	-.248	.091	1.000	.132	-.716	.418	-.249	.499	-.038
B3	.000	.087	.381	-.464	.446	.132	1.000	.247	.155	.196	.293	.484
B4	-.285	-.387	.223	.322	.564	-.716	.247	1.000	-.452	.285	-.523	-.067
B5	.396	-.222	-.235	.153	-.362	.418	.155	-.452	1.000	.113	.057	.135
C1	.400	-.187	.156	.000	.000	-.249	.196	.285	.113	1.000	-.700	-.109
C2	-.100	.607	.000	-.542	-.046	.499	.293	-.523	.057	-.700	1.000	.381
C3	-.109	.158	-.424	-.270	.000	-.038	.484	-.067	.135	-.109	.381	1.000

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	1.000 ^a	1.000	1.000	.00000

a. Predictors: (Constant), A4, A3, A1, A2

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.306	4	.577	.	b
	Residual	.000	5	.000		
	Total	2.306	9			

a. Dependent Variable: First_dimension

b. Predictors: (Constant), A4, A3, A1, A2

Coefficients^a

Model		Unstandardized Coefficients	Standardized Coefficients	t	Sig.
1	(Constant)	١٦.٢٣١٠		.	.
	A1	.250	.736	.	.
	A2	.250	.788	.	.
	A3	.250	.708	.	.
	A4	.250	.815	.	.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	1.000 ^a	1.000	1.000	.00000

a. Predictors: (Constant), B5, B3, B2, B1, B4

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7.681	5	1.536	.	b
	Residual	.000	4	.000		
	Total	7.681	9			

a. Dependent Variable: Second_dimension

b. Predictors: (Constant), B5, B3, B2, B1, B4

Coefficients^a

Model		Unstandardized Coefficients	Standardized Coefficients	t	Sig.
1	(Constant)	١٦.٢٣١٠		.	.
	B1	.250	.442	.	.
	B2	.250	.404	.	.
	B3	.250	.412	.	.
	B4	.250	.424	.	.
	B5	١٦.٢٣١٠	.000	.	.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	1.000 ^a	1.000	1.000	.00000

a. Predictors: (Constant), C3, C1, C2

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4.322	3	1.441	.	b
	Residual	.000	6	.000		
	Total	4.322	9			

a. Dependent Variable: Third_dimension

b. Predictors: (Constant), C3, C1, C2

Coefficients^a

Model		Unstandardized Coefficients	Standardized Coefficients	t	Sig.
1	(Constant)	١٦.٢٣١٠		.000	1.000
	C1	.333	.777	81737799.542	<.001
	C2	.333	.777	76032387.827	<.001
	C3	.333	.659	97287440.889	<.001