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Autonomous Vehicle Technology and Technology Acceptance: The Role of Technological Readiness on Consumers' Attitudes Towards Driverless Cars and Intention to Use in the Future

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Abstract: Autonomous (driverless) cars, which have entered the automotive industry with the developments in automotive and the advancement of artificial intelligence technologies, are rapidly finding a place in the marketing field. At this point, there are factors affecting consumers' concerns and willingness to use autonomous vehicles. In order to discover these factors, the readiness of consumers and the aspects in which they are ready for this technology are issues that need to be investigated. As a result of this situation, consumers' readiness to use autonomous vehicles, their attitudes toward using them, and their intentions to use them in the future are essential. This study aims to reveal the factors affecting consumers' attitudes and intentions towards using autonomous cars. Research data was collected via an online survey method. The convenience sampling method was used in the research. The research model was tested by structural equation modeling using Smart PLS. As a result of the research, it was found that discomfort and distrust dimensions significantly and negatively affected consumers' attitudes towards usage. It was found that the dimensions of optimism, innovativeness, and anthropomorphism significantly and positively affected consumers' attitudes toward use, and users' attitudes towards use significantly and positively affected their intention to use. The research results show that brands that put autonomous cars on the market should give importance to improvements in the dimensions of optimism, innovation, and anthropomorphism and should make improvements that will eliminate consumers' discomfort and insecurity.

Key words: Autonomous vehicles, Technology readiness index, Anthropomorphism

Otonom Araç Teknolojisi ve Teknoloji Kabulü: Tüketicilerin Sürücüsüz Araçlara Yönelik Tutumları ve Gelecekte Kullanım Niyeti Üzerinde Teknolojik Hazırlığın Rolü

Öz: Otomotivdeki gelişmeler ve yapay zeka teknolojilerinin ilerlemesiyle otomotiv sektörüne giren otonom (sürücüsüz) arabalar, pazarlama alanında hızla kendine yer bulmaktadır. Pazarda hızla gelişmesine rağmen, tüketicilerin kaygılarını ve otonom araç kullanma isteklerini etkileyen faktörler mevcuttur. Bu faktörlerin keşfedilebilmesi için tüketicilerin bu teknolojiye hazır olup olmadıkları ve hangi yönleriyle bu teknolojiye hazır oldukları araştırılması gereken konulardır. Bu durumun bir sonucu olarak tüketicilerin otonom araç kullanmaya hazır olmaları, kullanıma yönelik tutumları ve gelecekte kullanma niyetleri önem taşımaktadır. Bu çalışma tüketicilerin otonom araç kullanımına yönelik tutum ve niyetlerini etkileyen faktörleri ortaya çıkarmayı amaçlamaktadır. Araştırma verileri çevrimiçi anket yöntemiyle toplanmıştır. Araştırmada kolayda örnekleme yöntemi kullanılmıştır. Araştırma modeli Smart PLS kullanılarak yapısal eşitlik modellemesi ile test edilmiştir. Araştırma sonucunda rahatsızlık ve güvensizlik boyutlarının tüketicilerin kullanıma yönelik tutumlarını önemli ölçüde ve olumsuz yönde etkilediği tespit edilmiştir. İyimserlik, yenilikçilik ve antropomorfizm boyutlarının tüketicilerin kullanıma yönelik tutumlarını anlamlı ve pozitif yönde etkilediği, kullanıcıların kullanıma yönelik tutumlarının ise kullanım niyetlerini anlamlı ve pozitif yönde etkilediği tespit edilmiştir. Araştırma sonuçları, otonom otomobilleri piyasaya süren markaların iyimserlik, yenilikçilik ve antropomorfizm boyutlarında iyileştirmelere önem vermesi ve tüketicilerin rahatsızlık ve güvensizliğini ortadan kaldıracak iyileştirmeler yapması gerektiğini göstermektedir.

Anahtar kelimeler: Otonom araçlar, Teknolojiye hazırlık endeksi, İnsanbiçimlilik.

1. Introduction

Our world, with the developing technology, we are entering a new era, the Digital Age. The industrial equivalent of these digital developments appears as the 4th Industrial Revolution. The aim here is to combine existing physical systems with the digital world and ensure that the highest efficiency is achieved at the lowest cost. In addition, targets aimed at reducing negative environmental consequences such as greenhouse gas emissions, decrease in agricultural productivity and climate change are also among the goals of Industry 4.0 [1,2].

One of the most important applications of digitalization, which was considered a dream in the past, is autonomous vehicles [3]. Autonomous vehicles, also called driverless or robot vehicles; They work with the help

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of sensors such as optical and thermographic cameras, radars, lidars, sonars, global positioning system (GPS) and inertial measurement system placed on the vehicle to detect the environment [4]. With the help of these sensors, they process road and environmental data and create a 3D data model of the environment where the vehicle is located. Depending on the model obtained, they determine the vehicle's traffic controls, its reaction to obstacles and other factors on the road, and the appropriate route with the help of complex algorithms and artificial intelligence-based software [5,6].

The Society of Automotive Engineers (SAE) has defined a vehicle's autonomous driving capabilities as six stages [7]. While level 0 is described as a fully driver-controlled vehicle, levels 1 and 2 are systems called driving assistants that support the driver in certain situations (cruise control, lane tracking system, etc.). Level 3 describes when vehicle control switches to autopilot in certain traffic conditions. When supports such as traffic congestion assistant highway driving control take control of the vehicle, the driver can rest in the vehicle. At this level, the driver can regain driving control in any adverse situation. Level 4 is where automatic systems perform driving control without any need for human intervention. At this level, the vehicle performs system control only under certain and predefined conditions; That is, autonomous controls will not work when the driving route or weather conditions change. In such cases, the driver can take control and the vehicle can continue driving according to redefined conditions. At the last level, Level 5, the vehicle operates completely autonomously without human interaction. These vehicles are generally robots used to transport people or goods. Autonomous vehicles, which are widely used today, are still considered level 2. As a result of the joint efforts of some automotive and software companies, level 3 vehicles have also been produced.

With the development of sensing sensors and software technology, autonomous vehicles will increase traffic safety and passenger comfort day by day; It is estimated that this will lead to a decrease in increasing traffic density in cities, fuel consumption that causes CO_x emissions, and thus air pollution [8,9]. In addition, it is predicted that it will cause a significant decrease in traffic accidents, which are one of the highest causes of injury and death in our country [10].

The realization of all these positive benefits depends on the smooth operation of the mentioned sensors and software-based artificial intelligence applications. For this reason, very comprehensive testing and development processes are carried out to increase the safety and reliability of the systems used in autonomous vehicles [11]. Many academics and industry leaders demand that standards in autonomous vehicles be defined and implemented in a strict and disciplined manner, as in the aviation and space sector. Some concerns among researchers and industry experts cause greater concerns among the end-user public [12,13]. The development of autonomous vehicles often involves a spiral system development process with great emphasis on regular and regressive system testing. This iterative approach allows for continuous improvement and development of the tool's capabilities [14]. It can be stated that this iterative approach and overcoming safety concerns played an important role in the widespread acceptance and perception of autonomous cars by the public. According to the research conducted by Hulse et al. in 2018 [14], it is seen that the perceptions of autonomous cars vary depending on the perspective of different road users. When the literature on perceived risks is analysed Moody et al. (2020) [15] in their study with more than 30,000 participants from 51 different countries to investigate public expectations about autonomous vehicles, they revealed that the public's autonomous vehicle safety perceptions and concerns are in different shapes and levels in different age groups and different income groups. Kyriakidis et al. (2015) [16] conducted a study with the participation of 5000 people from 109 countries on user acceptance, concerns and purchasing desires about partially autonomous, highly autonomous, and fully autonomous vehicles. Depending on the variables they determined such as age, gender, and personality traits, they revealed the users' desire to buy an autonomous vehicle, their concerns about the autonomous vehicle and their financial expectations. Cunningham et al. (2019) [17] published their study with more than 6000 participants in New Zealand to determine the preference for paying for autonomous driving technologies and to determine attitudes and concerns about autonomous vehicles. The aim of the study was to measure the reactions of different sociodemographic participants regarding the benefits of autonomous vehicles, concerns about autonomous vehicles, conditions of use and paying for this technology. Many studies have been carried out and continue to be carried out to examine the concerns, expectations and preferences of the society, passengers and other vehicle drivers who share the same road with autonomous vehicles [18,19]. Factors such as gender, age and risk-taking behavior can affect the perceived risk and acceptance of autonomous vehicles.

In this study, to make a significant contribution to the literature, the direction in which consumers' positive and negative perceptions towards autonomous vehicle technology will evolve will be examined with the research model created using the literature review. Optimism and innovation, which express positive perceptions, and discomfort and insecurity, which express negative perceptions, of the technological readiness index will be used for the technological readiness of consumers. Additionally, it will be investigated whether consumers attach importance to artificial intelligence displaying human-imitating features. As a result of all this research, with the advancement of technologies that have just reached the 3rd level of the 6-level autonomous driving ability mentioned above [7] with technological developments and the transition to the next autonomous driving levels, a prediction is made about the direction in which consumers' attitudes will be shaped and the activity in the sector is presented. Suggestions will be presented to businesses that are willing to enter the Türkiye market and that they may need to direct consumers' intention to use their brands in the future.

1.1. History of autonomous vehicles

The first experiments on autonomous vehicles started in the 1920s. The studies carried out at this time were mostly on driverless vehicles that could be controlled by remote control. Technology, which progressed with small steps from this date until the 1980s, gained momentum in the 1980s with the development of automated systems on highways and the related efforts to develop new automation functions based on the vehicle-highway relationship. It has become more widespread after the 80s, when many automotive manufacturers developed autonomous systems at different levels and functions. Nowadays, after the 2000s, autonomy has become much more visible, especially with the development of electric vehicles. In recent years, with the advancement of technology and application areas, more autonomous vehicles have begun to appear on the roads [20,21].

1.2. Autonomous vehicle technologies

Autonomous vehicles are vehicles that can perceive their environment and surrounding data and perform various functions by making decisions based on this data they perceive, without any human intervention [22]. These vehicles, which can detect the environment and surrounding conditions while driving through advanced technologies such as sensors, detectors, cameras, global positioning systems (GPS), lidar and radar, guide the vehicle and make the necessary decisions against existing or instantaneous factors in the environment with software-based artificial intelligence. They enable the tasks to be carried out [23].

Intensifying traffic, increasing fatal accidents and traffic safety concerns due to the increasing population, drivers believe that some vital functions in vehicles being performed by software-based computers with a lower margin of error will increase driving comfort and safety. In order to meet these expectations, researchers and manufacturers have begun to work on the production of systems and vehicles that feature different levels of autonomy and have managed to achieve significant results in the field of autonomous driving technologies, especially in the last 20 years.

The Society of Automotive Engineers (SAE) defines autonomous control in vehicles as 6 levels [24].

- Level 0: There is no autonomy at this level, the vehicle is operated manually under the control of the driver.
- Level 1: It is the level where any vehicle feature is automated to assist the driver. The best examples of this level of autonomy are cruise control and speed limiters. Autonomous systems at this level are activated or deactivated by the intervention of the driver.
- Level 2: Like the first level, this is the level where certain features are automated and driving control primarily belongs to the driver. Unlike Level 1, at this level, the automated feature is automatically activated in situations previously defined by the software. But still the driving initiative lies with the driver.
- Level 3: This is the level called conditional automation. The vehicle takes the driving initiative in certain driving conditions. Autonomous systems such as highway driving assistant and traffic jam assistant take control of the vehicle under defined conditions and undertake many driving-related tasks. However, at this level, although the driving control is in the vehicle, the driver must take control of the driving in some situations and negativities.
- Level 4: At this level, called high automation, dynamic driving functions are performed by the system fully automatically, without human intervention, in predefined environments and scenarios. Automation will not work when exiting the specified environment or scenario. In cases where autonomous driving systems are not functional or when requested by the driver, control of the vehicle passes to the driver.
- Level 5: It is the full automation level. At this level, all driving functions of a vehicle are completely autonomous, without human intervention.

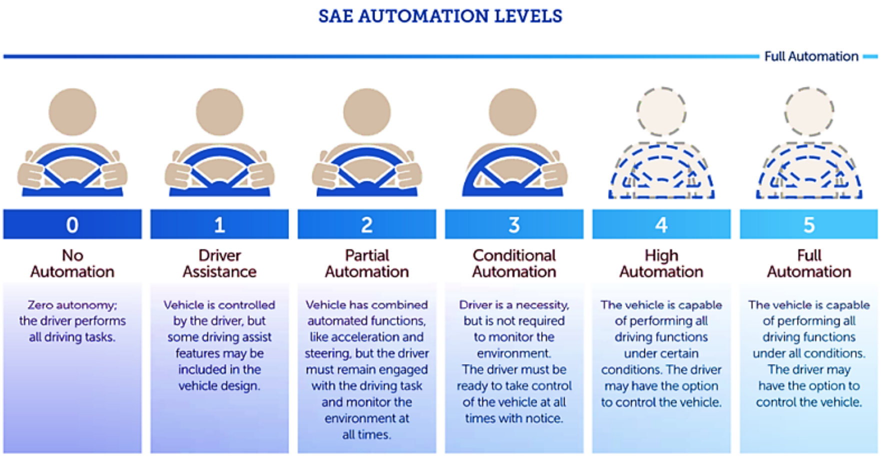

Figure 1. Automation levels specified in the SAE J3016 standard [24].

Data collected from sensors on driverless or autonomous cars are processed in real time to provide a detailed understanding of the environment. The information collected from the sensors is then analyzed and interpreted by the vehicle's artificial intelligence system. This system uses machine learning and probabilistic reasoning techniques to make decisions and control the vehicle's movements [25]. Artificial intelligence system can recognize and interpret traffic signs, signals, and road signs, as well as predict the behavior of other road users [14]. The decision-making process in autonomous vehicles involves multiple layers of planning. The mission planning layer determines the vehicle's overall goal or destination, while the behavioral layer determines when to change lanes, how to navigate intersections, and performs error correction maneuvers. The movement planning layer selects actions to avoid obstacles while moving towards local targets [26].

Planning layers in autonomous vehicles work together to ensure safe and efficient navigation. Extensive testing and development processes are carried out to ensure the safety and reliability of autonomous cars. The development of autonomous vehicles generally involves a spiral system development process with great emphasis on regular and regressive system testing [26]. This iterative approach allows for continuous improvement and development of the tool's capabilities. It can be stated that this iterative approach and overcoming safety concerns played an important role in the widespread acceptance and perception of autonomous cars by the public. In summary, the working principle of driverless or, in other words, autonomous cars involve the use of sensors, artificial intelligence and advanced algorithms to perceive the environment, make decisions and control the movements of the vehicle. Extensive testing and development processes are carried out to ensure security and reliability. Public perception and acceptance of autonomous cars also play an important role in their adoption.

1.3. Technological readiness index

The Technology Readiness Index (TRI), developed as 36-item scale measuring individuals' tendencies to adopt and use the latest technologies, was first published in the Journal of Service Research in 2000 [27,28]. Later, the questions in the scale were developed, their numbers increased and detailed and the TRI2 scale was published in 2015 [29]. TRI basically consists of four main factors: optimism, innovativeness, discomfort, and insecurity [30,31]. It has been researched and found in many studies that these factors affect individuals' attitudes towards technology and their readiness to adopt new technologies. The Technology Readiness Index (TRI), developed as 36-item scale measuring individuals' tendencies to adopt and use the latest technologies, was first published in the Journal of Service Research in 2000 [27,28]. TRI scale It has been researched and found in many different studies. For example, Lam et al. (2008) [32] highlighted that the TRI, as an aggregated measure of the four TR constructs, is positively related to consumers' acceptance of various technology-based products and services. Furthermore, the TRI has been utilized in diverse contexts, such as in predicting and explaining individuals' continuous use of self-service technologies [33], understanding travelers' behavior for sustainable smart tourism [34], and assessing the readiness of users for new technology in different settings [35]. The TRI has also been found to have meaningful relationships with the adoption of cryptocurrency Alharbi & Sohaib (2021) [4] and to affect customer perceived value [36]. This scale, especially technology readiness, is one of the scales that is accepted in the evaluation of new technologies by consumers and on which many studies have been conducted in the literature [37-49].

1.4. Attitude, Intention and Technology Readiness Index

The concept of attitude and intention in the context of consumer behavior and technological readiness is crucial in understanding the factors that influence individuals' acceptance and use of technology. Attitude refers to individuals' overall evaluation or feeling of favorableness or unfavorableness towards using a particular technology. At the same time, intention represents an individual's readiness to perform a given behavior, such as adopting or using a specific technology [50]. In the context of consumer behavior and technological readiness, these concepts play a significant role in shaping individuals' decisions regarding the adoption and use of technology. The Technology Readiness Index (TRI) is a well-established framework that assesses individuals' readiness to embrace and use technology. It comprises four dimensions: optimism, innovativeness, discomfort, and insecurity, collectively influencing individuals' attitudes toward technology [51]. These dimensions are essential in understanding consumers' predispositions towards technology and their willingness to engage with it.

Moreover, the TRI has been integrated into various models, such as the Technology Acceptance Model (TAM), to predict individuals' intentions to adopt and use technology [52]. The relationship between attitude and intention is evident in consumer behavior and technological readiness. Studies have shown that individuals' attitudes toward technology significantly influence their behavioral intentions [53]. For instance, consumers with positive attitudes towards a specific technology are more likely to express intentions to adopt and use it. Additionally, the TRI has been identified as a robust predictor of technology-related behavioral intentions and actual behaviors [54]. This underscores the importance of understanding individuals' attitudes and intentions regarding technological readiness and consumer behavior. Briefly, attitude and intention are integral to understanding consumer behavior and technological readiness. The TRI, with its dimensions of optimism, innovativeness, discomfort, and insecurity, provides a framework for assessing individuals' readiness to embrace technology while influencing their attitudes and intentions toward its adoption and use. Integrating the TRI with other models further enriches our understanding of the complex interrelationships between attitudes, intentions, and technology acceptance.

2. Literature Review, Research Model and Hypotheses

Autonomous cars have been the subject of numerous studies on various aspects such as perceptions, safety, decision-making, traffic flow and public acceptance. One study by Hulse et al. (2018) [14] focused on perceptions of autonomous vehicles, particularly in relation to vehicle users, risk, gender, and age. The findings of this study, conducted in the United Kingdom, shed light on acceptance and safety concerns regarding autonomous cars. In another study, Schwarting et al. (2018) [9] draws attention to the planning and decision-making processes involved in autonomous vehicles. This study highlights the need for extensive testing and notes that hundreds of millions of kilometers of testing, which could take several years to complete, may be required to ensure safety. Interactions between autonomous and human-driven vehicles have been examined through game theory modeling study [55]. This research aimed to verify and validate the control systems of autonomous vehicles by considering the dynamics between conventional and autonomous vehicles. The impact of autonomous driving on the public's mental health was investigated in a study [56]. Factors affecting public acceptance of autonomous driving were analyzed and its effects on the psychological well-being of the public were examined. There are many studies focusing on the effects of autonomous vehicles on traffic flow. In one study, Muhammad et al. (2022) [57] included micro-autonomous vehicles in a model called the cellular automaton model to evaluate the effects of autonomous cars on traffic congestion and highway capacity. Another study by Muhammed et al. (2020) [58] simulated the impact of autonomous vehicles, including autonomous buses, on traffic flow characteristics. Studies have been conducted from various perspectives to understand the social acceptance of autonomous vehicles. Tan et al. (2019) [59] investigated choice behavior based on logistics models, considering participants' personal characteristics, travel demand, and cognitive aspects of autonomous vehicles. Another study by Asadi-Shekari et al. (2022) [60] applied machine learning to explore emotions about sharing the road with autonomous vehicles as a cyclist or pedestrian. Azevedo et al. (2016) [61] conducted a study focusing on the microsimulation of the supply and demand of autonomous mobility on demand.

Moreover, when evaluated in the context of artificial intelligence, in recent years there has been an increasing interest in the impact of innovation on attitudes towards the use of technology, autonomous devices and artificial intelligence (AI). Various studies have examined the relationship between these constructs and found that the perceived usefulness, consumers' benefits, and innovativeness of these technologies can promote positive attitudes and increase the willingness to use [62-65]. For example, Wu et al. (2021) [62] found that the perceived usefulness of autonomous driving technology positively affects individuals' attitudes towards autonomous vehicles and their willingness to use them. Similarly, Zhang et al. (2021) [63] extended the Unified Theory of Technology Acceptance and Use model and found that risk expectation and consumer innovativeness are influential factors in the acceptance of autonomous vehicles. The development of autonomous vehicles has been facilitated by advances in artificial intelligence (AI) and machine learning (ML) technologies [66-68]. The cybersecurity of autonomous vehicles has also been a matter of debate. Additionally, Ma et al. (2020) [68] conducted research on artificial intelligence applications in the development of autonomous vehicles and highlighted various artificial intelligence techniques used in the perception, decision-making and control systems of autonomous vehicles. The impact of autonomous vehicles and artificial intelligence technologies extends beyond individual attitudes and usage. Acceptance and adoption of autonomous vehicles and artificial intelligence technologies is affected by various factors such as individual determinants, psychological factors and demographic characteristics. Golbabaei et al. (2020) [64] conducted a systematic review of the literature and revealed individual determinants of public acceptance and usage intention of autonomous vehicles, such as exposure to in-vehicle technologies. Huang (2023) [65] investigated the psychological factors affecting users and found that potential users' intentions to use autonomous vehicles and usability and technology acceptance model are important factors. Additionally, Meidute-Kavaliauskiene et al. (2021) [69] conducted a survey study on autonomous vehicles, finding that younger respondents with a tech-savvy background were more likely to have a positive attitude towards autonomous vehicles. Additionally, Erskine et al. [70] applied the unified theory of technology acceptance and use (UTAUT2) to evaluate consumer attitudes and behavioral intentions towards autonomous vehicles. This study highlights the importance of security and technology acceptance in shaping consumer attitudes. Becker and Axhausen (2017) [71] discussed consumers; attitudes towards autonomous vehicles, providing insight into various models and public perceptions [71,72].

When the local literature is examined, Nasır and Özçelik (2017) [73] investigated the perceived benefits, concerns, and users' attitudes about autonomous vehicles by conducting an online survey with 290 people across Turkey. According to the study results, although 89% of the survey participants had heard of driverless vehicles, only 23% stated that they knew about them. While the majority of participants (67%) found driverless vehicles attractive, 13% did not find them attractive. It can be stated that the essential benefits of driverless vehicles are that they can solve the transportation problems of elderly and disabled people, they can spare time for other activities during travel, and they can go to the desired place while drunk or sick. However, the study participants were most concerned about potential threats to their vehicles and system security from hackers. Despite these concerns, it can be stated that consumers' intentions to use driverless vehicles are observed positively.

Also, Yiğit et al. (2020) [74] aimed in their study to determine the limits of driverless vehicle technology in the field of public policy, examine its actors and market size, evaluate its potential to reduce problems such as fatal accidents and traffic-related greenhouse gas emissions in urban areas, and also determine the legal problems and externalities that this technology may cause. With the proliferation of autonomous vehicles, security problems, surveillance, privacy, data security, and cyber-attacks are also on the agenda. The legal situation in accidents involving autonomous vehicles and the moral dimension of artificial intelligence-supported decisions is also discussed. In the study, ethical principles determined by the German Autonomous Driving Ethics Commission were also evaluated, and suggestions for public policies were presented [74]. Moreover Kocagöz et al. (2020) [75] state in their studies that with the digital transformation in transportation, global strategic collaborations are increasingly becoming strong actors in the intelligent transportation ecosystem. In this context, it is stated that Turkey's Automobile Enterprise Group (TOGG) was established in Turkey in 2018 with six partners, and electric vehicles were introduced at the end of 2019. In this study, we tried to reveal consumers' first impressions and evaluations of the vehicles developed by TOGG. In the study, which was conducted using interviews, one of the qualitative research methods, subjects such as the participants' first reactions to the vehicles, the features they emphasized, price estimates/expectations, purchase intentions, and brand recommendations were examined. According to the study results, it is thought that TOGG's local and national emphasis impacts its marketing communication strategy. It is stated that consumers are generally optimistic about TOGG tools, but the results of this study do not represent all consumers, and more comprehensive research is needed. It is stated that autonomous vehicles entered our lives with Tesla brand cars by Elon Musk [76]. Şener (2023) [77] provides a comprehensive literature review on current studies in autonomous shared vehicle management systems, shedding light on the developments and challenges in this field. Additionally, Semiz and Öztürk (2023) [78] emphasize that legal regulations regarding autonomous vehicles in Turkey should be made soon and draw attention to the importance of addressing legal issues in the transition to autonomous driving. Additionally, Ecevit (2023) [79] investigates consumer acceptance of autonomous delivery vehicles using theoretical models such as the Unified Theory of Technology Acceptance and Use (UTAUT) and Technology Acceptance Model (TAM) to understand consumer behavior toward autonomous vehicles. The focus is on developing logical decision-makers and rules bases for the safe navigation of autonomous vehicles. The importance of modeling driver behavior for the safe use of autonomous vehicles is emphasized [80]

Additionally, Özçevik et al. (2023) [81] analyze simulation environments for autonomous vehicle design, providing insight into the various capabilities and differences of existing simulation environments. Additionally, Uçarlı et al. (2022) [82] emphasize the role of multiple GNSS satellite systems in ensuring accurate positioning, emphasizing the importance of precise and reliable positioning of autonomous vehicles, especially in challenging urban environments. Additionally, Akkaya and Özbay (2022) [83] investigate the impact of autonomous vehicles on innovative transportation policies, pointing to a holistic approach to understanding the broader impacts of autonomous vehicles on transportation policies.

These studies show that autonomous cars are examined in various fields such as technology, urban sustainability, public health, traffic, and transportation policies. As autonomous cars become more widespread, more research and legislation need to be made in these areas. The potential impacts of autonomous vehicles and policy preparations in this context have been examined in the literature. As a result, studies on autonomous cars;

It covers a wide range of topics, including perception, safety, decision-making, traffic flow and public acceptance. These studies provide valuable information on various aspects of autonomous vehicles, and ongoing research and development in this field contributes to the literature. This study aims to make a significant contribution to the literature as it is a different study measuring consumers' readiness for technology and using structural equation modeling on autonomous cars. This research is an original study in this respect. In order to measure consumers' readiness for new technologies, the relationship between the research variables is summarized below and the research model was created accordingly.

2.1. The effect of innovativeness on attitude towards usage

Consumer innovativeness refers to consumers' willingness and ability to adopt and use new products or ideas [84]. Various studies have found that consumer innovativeness has a positive effect on attitude. Soo (2020) [85] found that hedonically motivated consumer innovativeness and socially motivated consumer innovativeness have positive effects on attitude and are strengthened by attractiveness, utility, subcultural appeal, and originality. Jansson (2011) [86] emphasized the potential of innovation to change both attitudes and behavior in the context of the adoption of ecological innovation. Kim et al. (2010) [87] revealed how consumer innovativeness and shopping enjoyment influence beliefs, attitudes, and behavioral intentions towards pop-up store retailing. Esfahani and Reynolds (2021) [88] found a weak negative relationship between social innovativeness and attitude, suggesting that socially innovative consumers may indeed respond negatively to new products. Additionally, consumer innovativeness was found to mediate the relationship between other factors and attitude. For example, Kim and Son (2021) [39] found that innovativeness had a positive effect on attitude, and self-responsibility mediated the relationship between ecological knowledge and innovativeness and attitude. Shams et al. (2020) [90] found that consumer-perceived brand innovativeness and consumer-perceived product innovativeness mediate the effect of brand attitude. Albarrán et al. (2021) [91] investigated the perception of artificial intelligence in Spain. Researchers used logistic regression analysis to analyze attitudes towards robots and artificial intelligence and their possible determinants. The research revealed that perception, innovation, place of residence, gender, age, education level and other socioeconomic and technical variables affect attitudes towards artificial intelligence. This study highlights the complex nature of attitudes towards AI and the various factors that may influence them. However, there are also studies that find inconsistent or mixed results regarding the relationship between consumer innovativeness and attitude. For example, Hirunyawipada and Paswan (2006) [89] noted that the effects of consumer innovativeness on adoption intention are somewhat inconsistent. Studies in the literature generally show that innovativeness has a significant and positive effect on attitudes towards usage.

2.2. The effect of optimism on attitude towards usage

Optimism is an important factor influencing attitudes towards technology adoption. Several studies have investigated the impact of optimism on attitude using the Technology Readiness Index (TRI) framework. A study was conducted by Moxley and Czaja (2022) [38] on older adults' decisions regarding the adoption of technology, and it was revealed that the optimism dimension in the technology readiness scale positively affects attitudes towards the adoption of technology. Similarly, Sani et al. (2021) [30] investigated technology readiness attitudes towards using mobile payment systems. In this study, they used the Technology Acceptance Model (TAM) and found that optimism, along with other factors, significantly affects the intention to use mobile payment systems. In the context of cryptocurrency adoption, Sohaib et al. (2020) [92] examined the relationship between technology readiness dimensions (including optimism) and intention to use cryptocurrency. They found that optimism positively affects cryptocurrency acceptance. Pires et al. (2011) [93], in their study investigating the differences between internet banking users and non-users and the antecedents of the technology acceptance model (TAM), found that optimism, along with other factors, played an important role in explaining the differences between technology users and non-users. The technology readiness index (TRI) framework developed by Parasuraman and Colby (2014) [27] includes optimism as one of the dimensions. In addition, a study conducted in the domestic literature found a significant and positive relationship between optimism and interest in Industry 4.0 [94].

Sinha et al. (2019) [95] in their study investigating mobile payments and the privacy factor in India, they revealed that optimism, as a part of individuals' readiness for technology, affects their intention to use mobile payments~~.~~ In summary, many studies show that optimism, as part of individuals' technology readiness, has a positive impact on attitudes towards technology adoption. This finding is consistent across many different technology-related areas, including mobile payments, cryptocurrency adoption, online banking, and digital learning. Optimism contributes to individuals' readiness to adopt and use technology, leading to the formation of positive attitudes towards the adoption of technology.

2.3. The effect of anthropomorphism on attitudes towards use

Anthropomorphism, the attribution of human-like characteristics to nonhuman entities, has been studied extensively in a variety of contexts, including its impact on attitudes toward autonomous cars. Various studies investigating the relationship between anthropomorphism and attitudes towards autonomous vehicles shed light on factors affecting trust, acceptance, and other attitudes towards these vehicles. Waytz et al. (2014) [96] found in their study that anthropomorphism increased trust in autonomous vehicles. Researchers conducted an experiment in which participants interacted with an autonomous vehicle that exhibited human-like characteristics and one that did not exhibit human-like characteristics. Results show that participants who interacted with the anthropomorphized vehicle reported higher levels of trust compared to those who interacted with the non-anthropomorphized vehicle. This suggests that anthropomorphism may play a role in shaping attitudes towards autonomous cars by increasing trust. Cheng et al. (2022) [97] investigated the effects of anthropomorphism level on drivers' perceived control, confidence and driving performance. Researchers conducted a driving simulation experiment in which participants interacted with robots that resembled humans at different levels. The results show that higher levels of anthropomorphism lead to increased confidence and perceived control, which in turn improves driving performance. This study strengthens the claim that anthropomorphism may have a positive impact on attitudes towards autonomous cars by increasing trust and perceived control.

Tian and Wang (2022) [98] conducted a study on the psychological determinants of users' adoption of autonomous vehicles from the perspectives of anthropomorphism and UTAUT (Unified Theory of Acceptance and Use of Technology). Researchers surveyed participants to assess their perception of anthropomorphism and their intention to adopt autonomous vehicles. The results show that consumers' perceptions of anthropomorphism positively influence their adoption intentions and highlight the role of anthropomorphism in shaping attitudes towards autonomous cars and their adoption. Finally, Niu et al. (2018) [99] found that anthropomorphizing information about autonomous vehicles can increase trust in these vehicles. Researchers conducted an experiment in which participants were exposed to different types of information about autonomous vehicles, including anthropomorphized information. Results show that participants who received information from a humanized vehicle perceived the vehicles as more trustworthy than those who received information from a non-anthropomorphized vehicle. This supports the idea that anthropomorphism may play a role in shaping attitudes towards autonomous cars by increasing trust. Besides trust and adoption intentions, anthropomorphism has been found to influence other attitudes towards autonomous devices. When the research conducted in the domestic literature is examined, Sönmez and Nart (2022) [100] defined the concept of Anthropomorphism in their study as attributing human characteristics to non-human entities. This study examined the conceptualization process of Anthropomorphism, its prevalence, explanation theories, and empirical research findings in the context of consumer behavior. Research findings show that companies' anthropomorphization of their products and brands produces positive consumer results. However, it has also been emphasized that anthropomorphic products and brands may sometimes lead to negative consequences. As a result of the study, it was stated that Anthropomorphism generally offers positive results for companies but has conditional effects on consumers, and the findings in the literature should be handled with caution unless replication studies support them. However, in the study by Kamran (2021) [101], no effect of the anthropomorphism dimension on attitude was found. Overall, studies in the literature provide evidence that anthropomorphism can have a significant impact on attitudes towards autonomous cars. Anthropomorphizing autonomous vehicles by giving them human-like characteristics can increase trust, perceived control, and adoption intentions. The results in the literature show that anthropomorphism has a significant and positive effect on attitudes towards using.

2.4. The effect of discomfort on attitudes towards use

Discomfort is an important factor to consider when investigating the impact on attitude regarding the Technology Readiness Index (TRI). Several studies have examined the relationship between discomfort and attitudes toward technology adoption. The study by Parasuraman and Colby (2014) [27] did not specifically focus on the impact of discomfort on attitude, but it provides a basis for understanding the role of discomfort in technology readiness. Kuo et al., (2013) [102] conducted a study on the acceptance of mobile electronic medical record systems among nurses. The study examined the effect of nurses' readiness for technology on their acceptance of these systems. Findings revealed that discomfort is one of the factors hindering technology readiness. This result suggests that discomfort may hinder the acceptance and adoption of new technologies, which in turn may affect attitudes towards technology.

Shin and Lee (2014) [103] investigated the effects of technology readiness and technology acceptance on NFC (near field communication) mobile payment services in Korea. Research has found that discomfort and insecurity are two inhibitors of technology readiness. These blockers have been found to have a negative impact on attitudes towards NFC mobile payment services. This also supports the idea that discomfort can influence attitudes towards technology adoption. In summary, numerous studies have shown that discomfort is an important factor that can influence attitudes towards technology adoption. When the studies in the domestic literature were examined, the study conducted by Yaykın and Tolay (2023) [104] investigated the relationship between technological readiness and employee performance. A survey conducted on 201 automotive industry workers determined that technological readiness has two dimensions: "optimistic-innovative" and "uncomfortable-insecure." According to the research results, it was found that the optimistic-innovative dimension increased the perceived employee performance (78%), while the uncomfortable-insecure dimension decreased it (12%). Additionally, it has been determined that the technology readiness level of white-collar employees is lower than that of blue-collar employees. In another study, discomfort, and insecurity, the negative dimensions of technology readiness, do not significantly affect perceived ease of use and usefulness. Finally, in a study investigating the relationship between personality traits and technology readiness, it was found that there was no significant relationship between discomfort and personality traits. These studies suggest that discomfort may act as a deterrent to technology readiness and negatively impact consumers' intentions to adopt new technologies. Studies in the literature generally show that discomfort has a significant and negative effect on attitudes towards use.

2.5. The effect of insecurity on attitude towards use

Kuo et al. (2013) [102] found that optimism and innovativeness facilitate technology readiness, while discomfort and insecurity play a hindering role. Similarly, Lima et al. (2018) [105] supported the TRI paradigm by stating that discomfort and insecurity of a technology have a negative relationship with technology adoption. Additionally, Sohaib et al. (2020) [92] examined the relationship between technology readiness dimensions (including insecurity) and intention to use cryptocurrency. It was found that the discomfort and insecurity dimensions of the technology readiness scale had significant and negative relationships with cryptocurrency adoption. Roy et al. (2018) [106] found that technology readiness does not directly affect customer attitude, but indirectly through perceived innovation features. This means that although insecurity does not directly affect attitude, it can influence individuals' perception of innovation, which in turn can influence their attitudes towards technology. Additionally, the study by Chen and Lin (2018) [107] was conducted by integrating the Technology Readiness Index (TRI) into the Technology Acceptance Model (TAM) to explain people's acceptance of new technologies. The study argues that TRI explains technology acceptance through the general tendencies of individuals, while TAM focuses on system-specific perceptions. This suggests that insecurity, as a dimension of technology readiness, may play a role in individuals' acceptance of new technologies. Contrary to this result, Şekkeli (2022) [108] found a positive effect of distrust in digital technologies on the perceived usefulness of digital transformation. In summary, studies on the impact of insecurity on attitude in the context of TRI suggest that insecurity acts as an inhibitor of technology readiness and may have a negative relationship with technology adoption and acceptance. However, its effect on attitude may be indirect, mediated by factors such as perceived innovation characteristics.

2.6. The effect of attitude towards use on intention to use

When examined in the context of artificial intelligence-based technologies, Behavioral Reasoning Theory (BRT) is used to examine the effect of attitude on intention [109-112]. For example, Anayat et al. (2023) [109] investigated context-specific reasons and consumer adoption of AI-based voice assistants using the Reasoning Theory approach and revealed that attitude plays an important role in the intention to use AI-based voice assistants. Similarly, Wagner et al. (2023) [110] conducted a configuration analysis to understand potential doctors' intentions to use AI in their future medical practices and revealed that a strong belief in the role of AI is required for the intention to use AI. Teo et al. (2016) [112] developed the expanded Theory of Planned Behavior and found that attitude towards computer use has a significant positive effect on technology use intention. Chin et al (2022) [113] investigated how the participation of sports facility users could be increased. In this study, they found a positive relationship between the intention to use artificial intelligence fitness services based on the Technology Acceptance Model and attitudes towards artificial intelligence services and purchase intention. Ho et al. (2022) [114], in their study examining the intention to adopt artificial intelligence-supported online environments, found that attitude has a significant effect on behavioral intention in the services offered by tourism and accommodation companies. It has also been found that attitude affects the intention to use in various areas. Liang et al. (2019) [115] examined the application of artificial intelligence in fashion and found that consumers' attitudes towards artificial intelligence positively affected their purchasing intentions towards artificial intelligence products. Li et al. (2016) [116], in their study investigating teacher candidates' intentions to adopt technology, found that attitude towards technology, technology self-efficacy and perceived ease of use significantly predicted their intention to adopt technology. Cosmo et al., (2021) [117] found that attitude towards mobile advertising does not have a direct effect on behavioral intention to use chatbots (chat robot software), but attitude towards chatbots mediates intention to use. In summary, numerous studies show that attitude plays an important role in intention to use. These findings highlight the importance of considering attitude when examining the adoption and acceptance of AI and similar technologies in various fields.

Some studies in the literature were conducted by evaluating technological readiness [14,38,69,91] as well as consumers' gender and age variables. Based on the literature review, the research model and research hypotheses were detailed and created as shown in Figure 2 below.

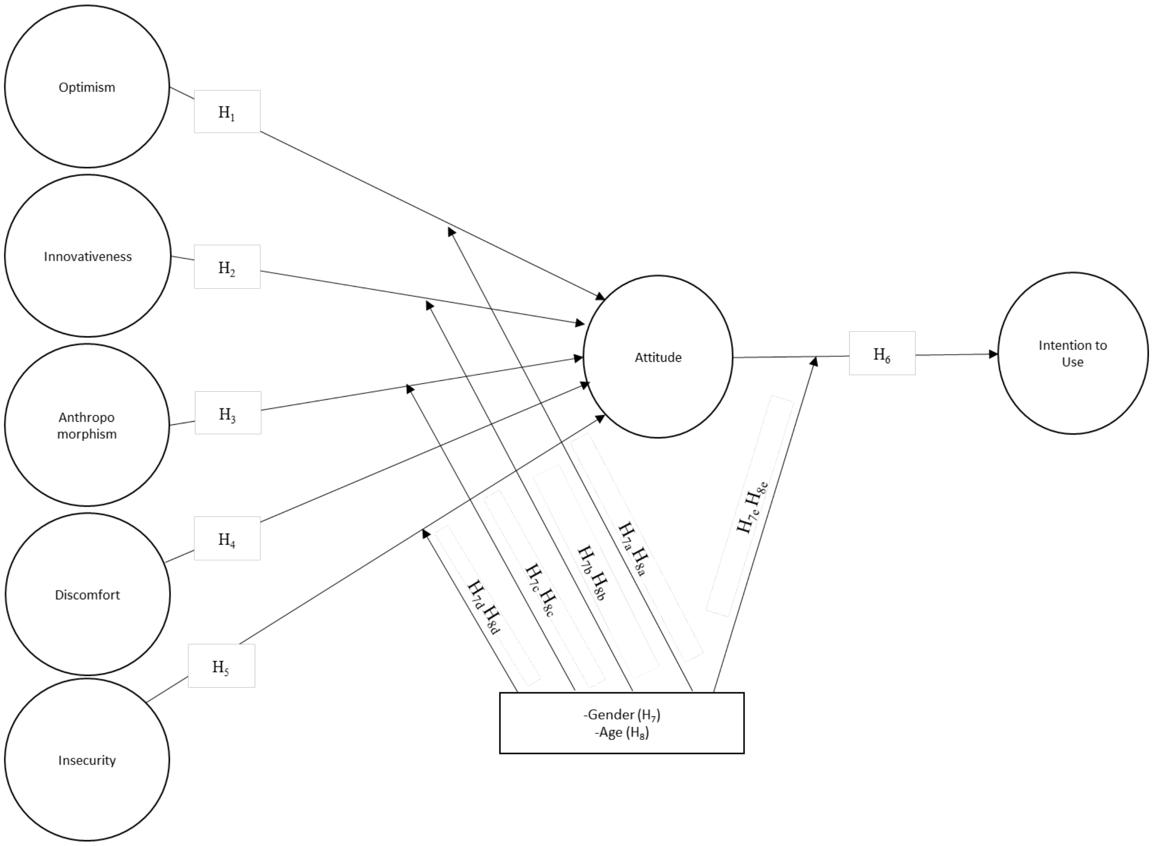

Figure 1. Research Model

H_1: Optimism towards autonomous cars has a significant and positive effect on consumers' attitudes towards using them.
H_2: Innovation towards autonomous cars has a significant and positive impact on consumers' attitudes towards using them.
H_3: Anthropomorphism towards autonomous cars has a significant and positive impact on consumers' attitudes towards using them.
H_4: Discomfort towards autonomous cars has a significant and negative impact on consumers' attitudes towards using them.
H_5: Insecurity towards autonomous cars has a significant and negative impact on consumers' attitudes towards using them.
H_6: The attitude dimension towards use has a significant and positive effect on consumers' intentions to use smart robot vacuum cleaners in the future.
H_{7a}: The effect of optimism on attitudes towards using varies by gender.
H_{7b}: The effect of innovativeness on attitude towards use varies by gender.
H_{7c}: The effect of anthropomorphism on attitudes towards using varies by gender.
H_{7d}: The effect of discomfort on attitudes towards use varies by gender.
H_{7e}: The effect of insecurity on attitudes towards use varies by gender.
H_{7f}: The effect of attitude towards uses on intention to use varies according to gender.
H_{8a}: The effect of optimism on attitude towards use varies according to age.
H_{8b}: The effect of innovativeness on attitude towards use varies according to age.
H_{8c}: The effect of anthropomorphism on attitudes towards using varies according to age.
H_{8d}: The effect of discomfort on attitudes towards use varies according to age.
H_{8e}: The effect of insecurity on attitudes towards use varies according to age.
H_{8f}: The effect of attitude towards uses on intention to use varies according to age.

3. Research Methodology

The aim of the research is to reveal the effect of consumers' technological readiness index dimensions (optimism, innovativeness, discomfort, insecurity) and anthropomorphism perceptions towards autonomous cars on their attitude towards using, and the effect of the attitude towards using dimension on their intention to use in the future. In this regard, it will be revealed how consumers' readiness for technology and their perception of anthropomorphism affect their attitude towards using it and their intention to use it in the future, and whether there are differences in the proposed research model according to gender and age variables. For this purpose, research hypotheses were determined by examining the literature and a research model was created according to the literature. As a result of the literature review, it is noticeable that this issue regarding autonomous cars has not been addressed in a holistic manner. Therefore, it can be stated that this study aims to make an original contribution in theoretical and practical terms.

The data collected in the research of this study was collected based on voluntary participation on consumers living in Turkey and aged 18 and over. No narrowing was made in the research other than these restrictions. Convenience sampling was used in the research. Convenience sampling is a widely used technique in research [118]. It involves selecting participants based on their convenience and accessibility rather than using a random or systematic sampling method. Convenience sampling is frequently used when researchers need to collect data quickly or when it is difficult to reach a representative sample [119]. The survey was kept open on Google forms between September 1 and September 15, 2023, for participants to answer, and the survey forms were collected during this two-week period.

The tenfold rule in the PLS path model refers to the rule that the sample size should be at least ten times the maximum number of internal or external model connections indicating any latent variable in the model. It is based on the assumption that a larger sample size is needed to ensure statistical power and stability in estimating parameters in SEM analysis [120]. However, it is important to remember that the adequacy of the sample size in SEM analysis may vary depending on the specific research context and the complexity of the model being tested [121]. Sample sizes below 100 are considered small, sample sizes between 100 and 200 are considered medium, and sample sizes above 200 are considered large [122]. In the model of this research, the maximum number of internal or external model connections pointing to any latent variable at the initial stage of the analysis is 12. Based on the tenfold rule, a sample containing 12 X 10 = 120 surveys meets the sample size to estimate the PLS path model. It can be stated that the sample number of this study, 141 participants, more than met this rule.

There are two separate sections in the survey form of the research. The first section includes questions to determine the demographic characteristics of the participants. In the second part, there are scale questions to measure the impact of the survey participants' technological readiness and anthropomorphism perceptions towards autonomous cars on their attitudes towards using and intention to use in the future. The scale questions are from the technological readiness 2 (TRI2) scale, which was developed by Parasuraman and Colby (2015) [29] and includes the dimensions of optimism, innovativeness, discomfort, and insecurity. The questions related to the anthropomorphism dimension were taken by Gursoy et al. (2019) [123] study, the questions regarding the attitude towards use dimension were taken from Rese et al. (2014) [124] and Taylor and Todd (1995) [125] studies, and questions regarding future use intention were adapted from Rese et al. (2014) [124] study. Ethics Committee Approval was received for the survey form used in the research from Bursa Uludağ University Research and Publication Ethics Committee on 25 August 2023 (decision number 23 taken in the 2023-07 session issue). The scale includes 54 statements and participants' responses were evaluated using a 5-point Likert scale (5 = Strongly Agree, 4 = Agree, 3 = Undecided, 2 = Disagree, 1 = Strongly Disagree). Data collected from participants was analyzed using Smart PLS 4.0 [126] software. Structural equation modeling was used to analyze the scale questions containing 54 statements.

4. Analysis Results

In the data analysis process, firstly, frequency analysis was carried out in the demographic data section of the survey. Then, measurement model analysis was applied to evaluate the reliability and validity of the scale dimensions in the second part of the survey. In the final stage of the research, the research model was tested using structural equation modeling.

4.1. Demographic characteristics of survey participants

Information on the demographic characteristics of the survey participants is presented in Table 1. When Table 1 is examined, it is seen that women (51.06%) and men (48.94%) participated in the research at similar rates. It is seen that there are more married (54.61%) respondents than single respondents, and the age group that participated most in the research consists of participants between the ages of 35-44 (36.17%). When the educational status of the participants is examined, it is seen that there is a high participation rate of participants with postgraduate education (42.55%). When looking at the income distribution, it is seen that there are more participants between 20,001 TL and 30,000 TL (28.37%), and although private sector employees (37.59%) and public employees (41.13%) show similar participation, the number of public sector employees is higher. According to Table 1, it is seen that 68.79% of the participants who answered the research questions own a car.

In the first of the open-ended questions asked to consumers, they were asked "the first brand that comes to their mind when it comes to driverless cars" without giving any clues, and the participants answered Tesla at a high rate (70.21%). In the second open-ended question, the participants were asked which traditional car brand they would trust to choose a driverless car produced by, and again without any hints, the most common answers were Volvo (30.50%) and Mercedes-Benz (17.73%).

Table 1. Demographic Distribution of Participants

Characteristics		N	%
Gender	Male	69	48,94%
	Female	72	51,06%
Marital Status	Married	77	54,61%
	Single	64	45,39%
Age	≤ 25	21	14,89%
	25-34	44	31,21%
	35-44	51	36,17%
	45-54	21	14,89%
	≥ 55	4	2,84%
Education	Primary and Secondary Education	3	2,13%
	High School	15	10,64%
	Associate degree	14	9,93%
	Bachelor's degree	49	34,75%
	Master's and Doctoral degree	60	42,55%
Income (Turkish Lira / TRY)	≤ 10.000	11	7,80%
	10.001– 20.000	22	15,60%
	20.001 – 30.000	40	28,37%
	30.001 – 40.000	32	22,70%
	40.0001 - 50.000	19	13,48%
	≥ 50.001	17	12,06%
Job	The Private Industry	53	37,59%
	The Public Sector	58	41,13%
	Student	11	7,80%
	Retired	2	1,42%
	Unemployed	3	2,13%
	Other	14	9,93%
Participants who own a car	Car Owner	97	68,79%
	Not a Car Owner	44	31,21%
The first brand that comes to mind when it comes to driverless and autonomous cars	Audi	2	1,42%
	BMW	3	2,13%
	Ferrari	1	0,71%
	None, I don't know, etc.	17	12,06%
	Honda	1	0,71%
	Mercedes-Benz	8	5,67%
	Porsche	2	1,42%
	Renault	1	0,71%
	Tesla	99	70,21%
	TOGG	3	2,13%
	Volvo	4	2,84%
Which of the traditional automobile brands would you trust to produce a driverless car?	Audi	7	4,96%
	BMW	8	5,67%
	None	7	4,96%
	Honda	3	2,13%
	Mercedes-Benz	25	17,73%
	Other (Ford, Hyundai, Mitsubishi, Peugeot, Renault, Seat, Suzuki)	9	6,38%
	Porsche	3	2,13%
	Tesla	8	5,67%
	TOGG	7	4,96%
	Toyota	13	9,22%
	Volkswagen	8	5,67%
	Volvo	43	30,50%
Total		141	100

4.2. Measurement model analysis results

In this study, a variance-based structural equation modeling method known as PLS-SEM (Partial Least Squares- Structural Equation Modeling) was used. The PLS-SEM method offers several advantages. First, it has a high degree of statistical power compared to CB-SEM (Covariance-based structural equation modeling), making it useful for researchers [127]. In addition, PLS-SEM is computationally more efficient than CB-SEM, which is advantageous in analyzing high-dimensional data [128]. The PLS-SEM method is increasingly used in fields such as quality management and is finding a place as a standard method with increasing interest [129]. PLS-SEM has the ability to analyze predictive models even with small data, which makes this method suitable for the analysis of predictive research [130]. It also stands out as a method that enables the discovery of complex relationships by allowing researchers to simultaneously identify, predict, and create regression models for hidden connections between input data [131]. PLS-SEM is flexible and can handle different measurement model setups, providing researchers with greater flexibility in their analysis [132]. It can also process models with both formative and reflective structures, making it suitable for the analysis of complex models [133]. Overall, PLS-SEM offers many advantages in terms of statistical power, ability to work with small samples, computational efficiency, flexibility, and ability to handle complex models.

Table 2. Measurement Model Analysis Results

Dimensions, Expressions and Abbreviations	Factor Loading	Cronbach's Alpha Value	Composite Reliability Value	Average Variance Extracted Value
Anthropomorphism				
Automobile artificial intelligence used for autonomous driving has its own minds/thoughts. (ANT1)	0,749	0,852	0,901	0,695
Automobile artificial intelligence used for autonomous driving has consciousness. (ANT2)	0,882			
Automobile artificial intelligence used for autonomous driving has emotions. (ANT3)	0,863			
Automobile artificial intelligence used for autonomous driving has its own free will. (ANT4)	0,834			
Optimism				
New technologies contribute to a better quality of life. (OPT1)	0,840	0,869	0,900	0,601
Technology gives people more control over their daily lives. (OPT3)	0,746			
I like technologies that allow me to adapt and organize work to my needs. (OPT6)	0,762			
Technology makes me more efficient in my profession. (OPT7)	0,764			
It is better to use products and services using the latest technologies than to use old technologies. (OPT9)	0,764			
I rely on technology to stay up to date on the issues I care about and stay on top of trends. (OPT10)	0,773			
Innovativeness				
People around me look to my knowledge for advice on new technologies. (INN1)	0,781	0,907	0,926	0,641
Generally, when a new technology emerges, I am one of the first in my circle of friends to use that technology. (INN2)	0,809			
I can usually understand new high-tech products and services without help from others. (INN3)	0,768			
I follow the latest technological developments in my areas of interest. (INN4)	0,856			
Solving and trying to understand high-tech devices gives me pleasure. (INN5)	0,844			
I realize that I have fewer problems than other people with the technological devices I use. (INN6)	0,793			
I prefer to use the most advanced technology available (INN7)	0,749			
Discomfort				
Caution should be exercised when replacing key people's duties with technology because new technology is unreliable. (DISCMF7)	0,890	0,629	0,841	0,727
I do not find it safe to do business with artificial intelligence. (DISCMF8)	0,813			
Insecurity				
I am concerned that the information I provide over the internet or to artificial intelligence may be misused by others. (INSCRT5)	0,733	0,822	0,872	0,579
When I call a business, I would rather speak to a human than to communicate with an automated AI system. (INSCRT7)	0,705			
When something is made autonomous or handed over to artificial intelligence, it is necessary to carefully check that the system does not make mistakes. (INSCRT8)	0,837			
Any transaction you make over the internet or to artificial intelligence must be confirmed later with a separate communication. (INSCRT9)	0,797			
I don't think it's safe to give personal information to AI tools. (INSCRT11)	0,723			
Attitude Towards Use				
It is a good idea to use artificial intelligence-supported autonomous cars for traveling or transportation. (ATT1)	0,794	0,899	0,930	0,769
I think that artificial intelligence-supported autonomous cars are a convenient tool that brings positive results to its users. (ATT2)	0,886			
I would be happy to use artificial intelligence-supported driverless (autonomous) cars. (ATT3)	0,907			
I think I would like to use artificial intelligence-supported driverless (autonomous) cars. (ATT4)	0,916			
Intention to Use in the Future				
I intend to use driverless cars for my travels in the near future. (INTENT1)	0,868	0,847	0,907	0,766
If I were to buy a car in the future, I would try driverless cars before deciding. (INTENT5)	0,837			
I am thinking of using driverless cars at the first opportunity. (INTENT6)	0,918			

Before proceeding with the research model analysis, the validity and reliability of the structures used in the study were evaluated. In this context, Cronbach Alpha coefficient and composite reliability (CR) coefficients were used for internal consistency reliability, and factor loadings of the statements and explained average variance values were calculated for convergent validity. If the factor loading of each statement exceeds the threshold value of 0.50, the Cronbach Alpha coefficient indicates high reliability between 0.70 and 0.90 and medium reliability between 0.50 and 0.70 [134,135]. It can be stated that the combined reliability (CR) should exceed the threshold value of 0.70. In addition, the average variance explained (AVE) value must exceed the threshold value of 0.50, these criteria are threshold values to ensure reliability and validity [136].

Expressions INT2, INT3, INT4, INSCRT1, INSCRT2, INSCRT3, INSCRT4, INSCRT6, INSCRT10, INN8, OPT2, OPT4, OPT5, OPT8 and OPT11, whose factor loadings did not exceed the threshold value of 0.50, were removed from the scale. The factor loadings of the remaining statements after the statements removed from the scale are above 0.50. As Table 2 is examined, it is seen that Cronbach's Alpha coefficient values are between 0.629 and 0.907, composite reliability (CR) values are between 0.841 and 0.926, and Average Variance explained (AVE) values are between 0.579 and 0.769. It can be stated that the values in the table are above the threshold values in the literature and the convergent validity criterion is met.

Criteria suggested by Fornell and Larcker (1981) [137] were used to determine discriminant validity. The discriminant validity results obtained according to these criteria are presented in Table 3.

Table 3. Discriminant Validity Results According to Fornell and Larcker Criteria

	Anthropomorphism	**Attitude**	**Discomfort**	**Innovativeness**	**Insecurity**	**Intention to Use**	**Optimism**
Anthropomorphism	**0,833**						
Attitude	0,304	**0,877**					
Discomfort	0,059	-0,444	**0,853**				
Innovativeness	0,128	0,352	-0,063	**0,801**			
Insecurity	-0,004	-0,347	0,497	-0,158	**0,761**		
Intention to Use	0,210	0,770	-0,294	0,368	-0,253	**0,875**	
Optimism	0,032	0,367	-0,293	0,293	-0,030	0,297	**0,775**

The results in Table 3 show that discriminant validity was met according to the Fornell and Larcker criterion. According to Table 3, since the square values of average value variance (AVE) explained are higher than the correlations with other structures, it can be stated that the structures measure different features and can be differentiated. This result shows that the structures used in the analysis are independent components and therefore the discriminant validity criterion is met.

The HTMT (Heterotrait-Monotrait Ratio) criterion proposed by Henseler (2017) [138] expresses the ratio of the correlations of expressions of all variables to the geometric averages of the correlations of expressions of the same variable. In order to ensure a valid model fit, HTMT coefficients should not exceed the threshold value of 1 [139]. When Table 4 is examined, it can be seen that the requirements of the HTMT criterion are met. Based on these results, it can be stated that the constructs used in the study have discriminant validity.

Table 4. Discriminant Validity Results According to HTMT Criteria

	Anthropomorphism	**Attitude**	**Discomfort**	**Innovativeness**	**Insecurity**	**Intention to Use**	**Optimism**
Anthropomorphism							
Attitude	0,339						
Discomfort	0,087	0,581					
Innovativeness	0,154	0,377	0,229				
Insecurity	0,096	0,385	0,686	0,198			
Intention to Use	0,244	0,842	0,407	0,413	0,280		
Optimism	0,150	0,395	0,382	0,326	0,118	0,331	

4.1. Structural equation model analysis results

The structural equation model of the research is shown in Figure 3. PLS-SEM method (Partial Least Squares Method) was preferred to examine the research model. The data obtained was analyzed using the Smart PLS 4.0 statistical program. PLS algorithm was used to calculate linearity and path coefficients as well as R2 and f2 values showing the effect of the research model. Additionally, the Q2 variable was calculated with PLSpredict analysis to measure predictive power. Bootstrap analysis was used to evaluate the significance of PLS path coefficients. Bootstrapping analysis was used to calculate dimension-specific t values by removing 5000 subsamples from the sample. The results of the research model are presented in the structural equation model table shown in Table 5.

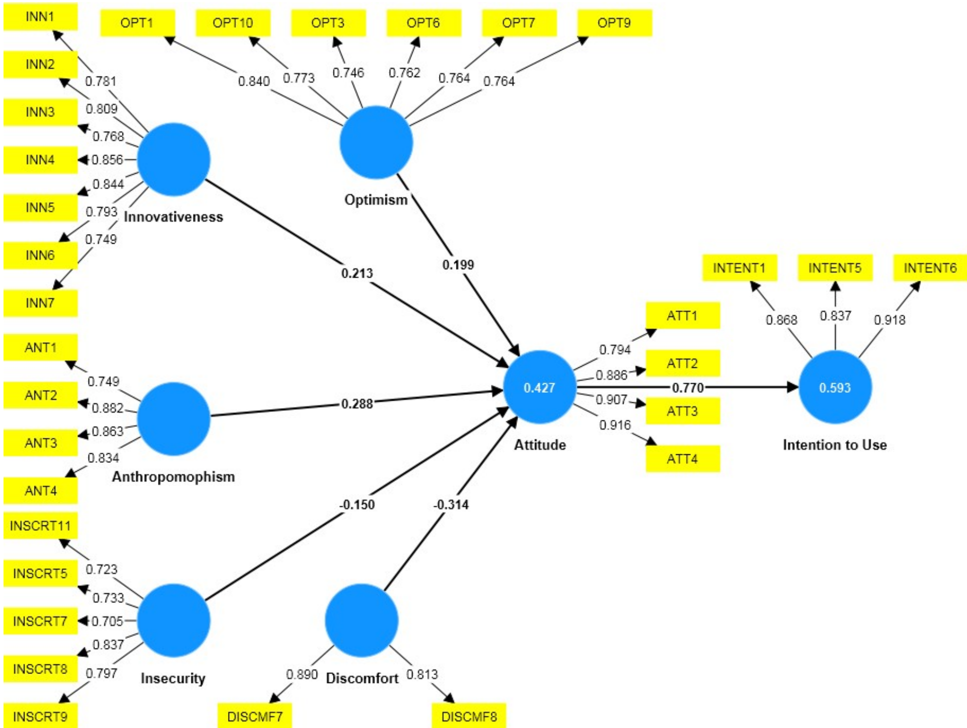

Figure 3. Measurement Model Analysis Results

Table 5. Structural Equation Modeling (PLS-SEM) Analysis Results

Hypothesis	Paths	Standardized β Coefficient	Standard Error	t Value	P Value	Result
H_1	Optimism -> Attitude	0,208	0,072	2,748	0,006	*Accept*
H_2	Innovativeness -> Attitude	0,216	0,067	3,181	0,001	*Accept*
H_3	Anthropomorphism -> Attitude	0,285	0,069	4,197	0,000	*Accept*
H_4	Discomfort -> Attitude	-0,308	0,074	4,249	0,000	*Accept*
H_5	Insecurity -> Attitude	-0,161	0,064	2,340	0,019	*Accept*
H_6	Attitude -> Intention to Use	0,772	0,059	12,978	0,000	*Accept*

According to Table 5, the t values of the accepted hypotheses are above the threshold value of 1.96 and therefore all hypotheses were accepted. These results show that four of the hypotheses were supported in a statistically significant and positive manner. It shows that two of the hypotheses are supported in a statistically significant and negative way.

The study examined the impact of various factors on attitudes towards autonomous cars, revealing significant findings. Optimism (β=0.208; $p<0.05$), innovativeness (β=0.216; $p<0.05$), and anthropomorphism (β=0.285; $p<0.05$) were found to influence attitudes towards usage positively. Conversely, discomfort (β=-0.308; $p<0.05$) and insecurity (β=-0.161; $p<0.05$) were negatively associated with attitudes toward usage. Furthermore, a positive attitude towards usage (β=0.772; $p<0.05$) significantly increased the intention to use autonomous cars in the future. These results underscore the significance of individual perceptions and attitudes in shaping the acceptance of autonomous car technology.

These results show that all of the hypotheses of the research model are supported, that is, all of the latent dimensions affect the latent dimension of attitude towards use and the latent dimension of intention to use in the future.Table 6 below shows the R^2, f^2, Q^2 and VIF values of the model.

There are different VIF values suggested in the literature to evaluate collinearity. While some studies recommend the maximum threshold value as 10 [140], others recommend a value below 5 [141-151]. In addition, there are studies that recommend a more stringent threshold value, such as below 3.3 [143,147,149,152]. According to Table 6, VIF values are below all threshold values in the literature. This result indicates that there is no multicollinearity problem between dimensions.

When the R2 values in the model are examined according to Table 6, it shows that consumers explain approximately 43% of the attitude towards using autonomous cars. The ratio of the attitude dimension towards using autonomous vehicles to explain the intention to use autonomous vehicles in the future is approximately 59%.

Table 5. R2, f2, Q2 and VIF values of the Structural Equation Model

Hypothesis	Paths	R^2	f^2	Q^2	VIF
H_1	Optimism -> Attitude	0,427	0,056	0,368	1,238
H_2	Innovativeness -> Attitude		0,069		1,154
H_3	Anthropomorphism -> Attitude		0,142		1,022
H_4	Discomfort -> Attitude		0,114		1,511
H_5	Insecurity -> Attitude		0,028		1,410
H_6	Attitude -> Intention to Use	0,593	1,458	0,216	1,000

According to Cohen (1988) [153], f2 values greater than 0.02 represent a small effect size, greater than 0.15 represents a medium effect size, and greater than 0.35 represents a high effect size. According to Table 6, that can be said the dimensions of optimism (0.056), innovativeness (0.069), anthropomorphism (0.142), discomfort (0.114) and insecurity (0.028) have low f2 values, while the effect size of attitude towards using autonomous cars (1.458) is high.

The Q2 value obtained by PLSpredict analysis aims to evaluate the predictive power of the model by excluding the data of an indicator block from the model [154]. To determine that the model has a successful predictive power, Q2 values must be greater than 0 ($Q2 > 0$). 0 is considered a threshold value. According to Table 6, the Q2 value of the optimism, innovation, anthropomorphism, discomfort and insecurity dimensions was found to be 0.368, and the Q2 value of the attitude dimension towards using autonomous cars on the intention to use it in the future was found to be 0.216. According to the analysis results, since Q2 values are above zero, it can be stated that the model has a successful predictive power for the relevant dimensions.

4.2. Multiple group analysis results

In this section, the effect of categorical variables such as gender and age on the research model is examined. For this purpose, SmartPLS's multiple group analysis module was used to understand how the research model might change according to these categorical variables. The results of the multiple group analysis performed for the determined categorical variable are stated below, and these results are presented and evaluated under the following headings.

4.4.1 Multiple group analysis results by gender

Multiple groups analyzes were applied to test the H7 hypothesis in the research model. It was investigated whether the six hypotheses put forward in the research model differ according to the gender variable. In this context, the data from the sample was divided into two different groups according to gender, one containing women ($N = 72$) and the other containing men ($N = 69$). Then, multiple group analysis was performed by gender.

The results of the analysis based on male and female participants are presented in Table 7, where the path coefficients, the differences between the path coefficients and the significance levels of the differences are shown in detail.

Table 7. Path Coefficients, Differences Between Path Coefficients and Significance Levels of Differences According to Gender Variable

Hypotheses	Paths	Standardized β Coefficient (Female)	Standardized β Coefficient (Male))	Difference Between Path Coefficients (Female - Male)	t Value (Female-Male)	p Value (Female-Male)
H_{7a}	Optimism -> Attitude	0,263	0,158	0,105	0,729	0,460
H_{7b}	Innovativeness -> Attitude	0,223	0,106	0,116	0,893	0,365
H_{7c}	Anthropomorphism -> Attitude	0,232	0,428	-0,196	1,325	0,169
H_{7d}	Discomfort -> Attitude	-0,192	-0,496	0,303	2,089	0,040
H_{7e}	Insecurity -> Attitude	-0,280	-0,062	-0,218	1,590	0,110
H_{7f}	Attitude -> Intention to Use	0,835	0,671	0,164	1,363	0,170

According to Table 7, in the H7d hypothesis of the differences between the path coefficients in terms of gender groups, it was found that there was a statistically significant difference between men and women ($p = 0.040 < 0.05$) in the effect of discomfort on the attitude towards use. The H7d hypothesis was accepted, the other hypotheses were rejected, and no significant difference was found according to gender in the other hypotheses.

Regarding the effect of discomfort on attitudes towards use, it is seen that male participants (β=-0.496) have more negative attitudes than female participants (β=-0.192) when they feel uncomfortable, and the difference between the path coefficients is 0.303. Additionally, when Table 7 is examined, it is seen that the t value of the accepted hypothesis is above the threshold value of 1.96.

4.4.1 Multiple group analysis results by age

Multiple groups analyzes were applied to test the H8 hypothesis in the research model. It was investigated whether the six hypotheses put forward in the research model differ according to the age variable. In this context, the data from the sample was divided into two different groups according to age, one containing participants aged 34 and under (N = 65) and the other containing participants aged 35 and over (N = 76). Then, multiple group analysis by age was performed.

The results of the analysis based on participants aged 34 and under and 35 and over are presented in Table 8, where the path coefficients, the differences between the path coefficients and the significance levels of the differences are shown in detail.

Table 8. Path Coefficients According to Age Variable, Differences Between Path Coefficients and Significance Levels of Differences

Hypotheses	Paths	Standardized β Coefficient (Ages 34 and under)	Standardized β Coefficient (Ages 35 and above)	Difference Between Path Coefficients (34 years and below - 35 years and above)	t Value (34 years and below - 35 years and above)	p Value (34 years and below - 35 years and above)
H_{8a}	Anthropomorphism -> Attitude	0,370	0,180	0,190	0,940	0,313
H_{8b}	Attitude -> Intention to Use	0,658	0,861	-0,203	1,928	0,056
H_{8c}	Discomfort -> Attitude	-0,299	-0,290	-0,008	0,056	0,948
H_{8d}	Innovativeness -> Attitude	0,160	0,238	-0,077	0,492	0,631
H_{8e}	Insecurity -> Attitude	-0,146	-0,209	0,064	0,441	0,663
H_{8f}	Optimism -> Attitude	0,195	0,210	-0,015	0,091	0,944

According to Table 8, when the research model was examined according to the age variable, it was observed that there was no significant difference between the dimensions. Hypotheses H_{8a}, H_{8b}, H_{8c}, H_{8d}, H_{8e} and H_{8f} were rejected. According to the analysis results, the age variable does not affect consumers' technological readiness, attitude, and intention to use it in the future.

5. Results

The results of the research show that many factors significantly affect individuals' attitudes towards autonomous vehicle use. The research results coincide with the results of the literature examined in the study. First of all, optimism has a positive and significant effect on attitude towards usage. Optimistic individuals are more likely to have a positive attitude towards autonomous cars because they appreciate the advantages and benefits this technology offers [14]. Second, innovativeness also has a positive and significant effect on attitude towards usage. People who appreciate the innovative features of autonomous vehicles are more likely to have a positive view of the use of this technology [155]. Consumers find the technological developments brought by autonomous vehicles attractive and are more open to adopting them. Third, anthropomorphism has a positive and significant effect on attitude towards use. When autonomous cars have human-like behavior or user-friendly interfaces, individuals are more accepting of this technology [156]. This is a result that highlights the importance of designing autonomous cars with human-like characteristics to improve user experience and acceptance. On the other hand, discomfort and insecurity have negative and significant effects on attitudes towards use. Possible difficulties in the use of autonomous vehicles, security and privacy concerns lead individuals to develop negative attitudes towards the use of this technology [157,158]. Safety issues also play an important role in the adoption of autonomous vehicles [154]. Additionally, the study revealed that attitude towards use positively and significantly affects the intention to use autonomous cars in the future. Individuals with positive attitudes towards autonomous cars are more likely to have the intention to use this technology in the future. This suggests a positive cycle in the acceptance of autonomous cars, where positive attitudes shape future usage intentions [159]. In summary, the results of the study show that optimism, innovativeness, and anthropomorphism have positive effects on attitudes towards autonomous vehicle use, while discomfort and insecurity have negative effects. However, based on the results of multi-group analysis, male participants have a more negative attitude than female participants when they feel uncomfortable about autonomous cars. Attitude towards use positively affects the intention to use autonomous cars in the future. These findings highlight the importance of considering individuals' attitudes and perceptions when designing and promoting autonomous vehicle technology. At this point, the following suggestions can be offered:

- Training and awareness programs should be organized to introduce driverless car technology to the society and raise awareness, especially by businesses that will enter the autonomous vehicle market. These programs should highlight the advantages and safety measures of autonomous vehicles, including technical aspects.
- To support the use of autonomous vehicles, campaigns and information efforts focusing on optimism, innovation and anthropomorphism should be carried out. Anthropomorphism, in particular, should be considered a key element that can help users form an emotional attachment to tools.
- Strategies should be developed to reduce feelings of discomfort and insecurity. The reliability and security measures of the technology should be explained to consumers and negative perceptions in the minds of consumers should be eliminated. For this purpose, marketing communication efforts should be used intensively by relevant businesses.
- Gender-sensitive campaigns and educational materials should be developed by taking gender differences into consideration. Especially situations where male participants feel uncomfortable should be addressed and insecurities in this regard should be tried to be eliminated.
- To increase the intention to use autonomous vehicles, improvements should be made to make it easier and more accessible.
- This issue should be further studied by researchers to further examine the effects of autonomous vehicles on society and pay attention to user feedback.

6. Conclusions and Discussion

Research results show that optimism positively affects attitudes towards using. Optimistic individuals have a more positive perspective on new technologies and artificial intelligence-supported autonomous cars. Since optimism is associated with hope and positive expectations for the future, it is understandable that these people are more open to new technologies and more willing to use them. In particular, individuals who believe that technology improves the quality of life see the advantages offered by artificial intelligence-supported autonomous cars and have a more positive attitude towards this technology. These findings indicate that optimism is an essential factor in the technology acceptance process and influences users' adoption and use of technology. The results show that innovativeness positively affects the attitude towards using. Innovative individuals have a more positive perspective on new technologies and artificial intelligence-supported autonomous cars. These people generally stand out with their interest in technology and ability to understand. Innovative individuals understand and use new products and services more efficiently by quickly adopting technology. Therefore, innovation ensures that individuals with a positive attitude towards new technologies, such as artificial intelligence-supported autonomous cars, are more willing to use these technologies. These findings indicate that innovativeness is an essential factor in the technology acceptance process and influences users' adoption and use of technology.

Research findings show that the idea of anthropomorphism positively affects attitudes towards using. Individuals with anthropomorphism views perceive artificial intelligence-supported autonomous cars more positively. These people may believe that artificial intelligence in cars has human-like characteristics, which causes them to have a more positive attitude toward technology. These findings suggest that anthropomorphism is essential in the technology acceptance process and influences how users perceive the technology.

Research findings show that the idea of discomfort negatively affects attitudes towards use. Individuals feeling discomfort perceive artificial intelligence-supported autonomous cars more negatively and avoid using this technology. The basis of this situation lies in individuals' security concerns about new technology. These results show that security concerns play an essential role in the users' technology acceptance process and determine their attitudes toward using the technology. Another result is that insecurity negatively affects the attitude towards using. Individuals with a feeling of insecurity perceive artificial intelligence-supported autonomous cars more negatively and avoid using this technology. The basis of this situation lies in individuals' concerns about the risk of misuse of the information they share over the internet or with artificial intelligence and their security concerns. These results show that security concerns play an essential role in the users' technology acceptance process and determine their attitudes toward using the technology. In addition, according to the research results, consumers are more negatively affected by the discomfort than the distrust dimension.

The first brand question that comes to mind when talking about driverless and autonomous cars in the research was asked to evaluate the general awareness and image of consumers towards certain brands, to determine which brands the participants identify with driverless and autonomous cars, and as an indicator of how the market is shaped. At this point, the vast majority of the participants answered Tesla (70.21%). In the second answer, 12.06 participants stated that they did not know a brand on this subject or could not think of one. Currently, the Tesla brand has a dominant advantage among Turkish consumers. Another singular question: "If you were to buy a driverless car, which of the traditional car brands would you trust?" question was posed to the participants. In this question, Volvo (30.5%) and Mercedes-Benz (17.73%) were the preferred car brands. This question measured consumers' trust and preferences regarding driverless car technologies. This question aims to determine which traditional car brands are perceived by consumers as reliable and strong technology leaders, understand future preferences and market competition, and evaluate the impact of marketing strategies. Research findings show that attitude towards use strongly affects future intention to use. Users' intentions to use driverless cars are closely related to their development of a positive attitude towards this technology. These results show that users' development of a positive perspective towards driverless cars increases their intention to use this technology in the future. In particular, users' positive thoughts about using artificial intelligence-supported autonomous cars strengthen their intention to use driverless cars. Therefore, when evaluating users' intention to use driverless cars, it is important to focus primarily on the finding that their attitudes towards using them are positive.

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