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Studying the Consequences of Adopting Smart Agricultural Technologies with the Moderating Role of Government Policies and Regulations

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Abstract

The agricultural sector is one of the areas where smart agricultural technologies are widely used. Smart farming technologies offer the potential to analyze agricultural data on a scale not previously possible. Adoption of smart farming technologies has the potential to improve productivity and profitability in agriculture, while also improving sustainability. Achieving this potential requires not only technological advancements, but also a thorough understanding of the consequences that the adoption of smart agricultural technologies should have. The aim of the present study is to study the consequences of adopting smart agricultural technologies with the moderating role of government policies and regulations. The statistical population of the research includes managers, experts, and specialists in the field of smart agriculture in Tehran and Alborz provinces, Iran. One of the methods for determining the minimum sample size is the ratio of the number of sample members to the number of questions in the research model or the N:q theory. Accordingly, considering the number of questionnaire items (27 questions), the sample size was estimated to be 270 people. The data collection tool is a questionnaire. The validity of the questionnaire was assessed in diagnostic, convergent and divergent terms, and the reliability of the questionnaire was also assessed using Cronbach's alpha coefficient and composite reliability. The research model was tested using the partial least squares method and Smart-PLS 3 software. The results of data analysis showed that the adoption of smart agricultural technologies has a positive and significant impact on workforce, economic, and environmental outcomes. Furthermore, government policies and regulations play a positive moderating role in the relationship between the adoption of smart agricultural technologies and workforce, economic, and environmental outcomes.

Keywords: Economic consequences, Environmental consequences, Smart farming, Technology adoption, Workforce consequences

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Introduction

Agriculture, as the cornerstone of human civilization and economy, plays a vital role in providing livelihoods for communities (Azadi *et al.*, 2021). However, traditional production methods today grapple with serious challenges such as climate change, water scarcity, and heavy reliance on energy (Mana *et al.*, 2024). In this context, traditional agriculture brings devastating climatic consequences through the widespread emission of greenhouse gases, including carbon dioxide, nitrous oxide, and methane (Lieder & Schröter-Schlaack, 2021). Moreover, the use of chemical fertilizers and pesticides has led to soil and water pollution, and by generating nutrient runoff and releasing pollutants such as ammonia, it endangers human health and ecosystems (Ma *et al*., 2021). Furthermore, land-use changes, such as deforestation and land drainage, not only exacerbate greenhouse gas emissions but also pose a direct threat to biodiversity. The continuation of this situation could pose a serious crisis for food security and public health by reducing biodiversity and degrading foundational resources. Consequently, transitioning from traditional to modern agriculture is an undeniable necessity to meet the needs of a growing population. This transformation, known as the "Fourth Agricultural Revolution," leverages advanced technologies to establish a link between economic productivity and environmental sustainability, thereby ensuring future food security (Lieder & Schröter-Schlaack, 2021; Sambas *et al.*, 2023).

Researchers have defined this process of digital transformation in agriculture in various ways, such as "digital agriculture", "Agriculture 4.0" or "precision agriculture" (Mana *et al.*, 2024). In fact, the digital agriculture industry is experiencing a dynamic period of development in terms of technology supply. This newer phase has been termed the "digitalization" stage, and it is expected to have a greater impact on social and institutional spheres that require, and are increasingly dependent on, digital technologies (Giua *et al.*, 2022). The latest technological evolution has defined agriculture as "smart agriculture"—a "cyber-physical system"—in which intelligent technologies are considered the core control components of the farm (Mana *et al.*, 2024). The concept of smart agriculture can be applied to the notion of a "Smart Planet" (Li *et al.*, 2023), which is defined by various technologies such as "Internet of Things Technology (IoT)", "remote sensing technology", "big data analytics technology", "robotics and automation", "cloud and edge computing" and "artificial intelligence". By leveraging sensors, analytical software, and internet connectivity, these technologies enable data analysis and processing, timely decision-making, and precise monitoring in the field of agriculture (Otieno, 2023; Khaspuria *et al.*, 2024). Therefore, the adoption of smart farming technologies is not merely about using technological tools; their key role in data collection and analysis is of fundamental importance (Putri & Zainuddin, 2024).

The adoption of smart farming technologies can alleviate operational challenges in agriculture, including reducing stress, workload, and the time required for farmers' activities (Balafoutis *et al*., 2020). By adopting these technologies, farmers will be able to overcome various obstacles and improve their overall well-being (Basir *et al.*, 2024). The primary goal of this modern approach is to increase crop production, minimize resource waste, and enhance profitability (Mutlaq *et al.*, 2022). The positive environmental consequences resulting from the adoption of smart farming technologies include optimizing irrigation, planting resilient varieties, employing soil and water conservation techniques, intelligently relying on data and climate forecasts, utilizing fertilizers correctly, and applying pesticides effectively and efficiently (De Pinto *et al.*, 2020; Fiawoo *et al.*, 2024). Consequently, smart agriculture has strong potential to increase agricultural productivity while maintaining sustainability and environmental compatibility (Navarro *et* *al*., 2020). This is achieved by reducing the consumption of resources such as water and energy, as well as by minimizing negative environmental impacts (Virk *et al*., 2020).

Considering the first aspect of the novelty of the present study, it can be stated that in previous research the consequences (outcomes) of adopting smart agricultural technologies have been examined less frequently, while most studies have focused on the factors (drivers or antecedents) and barriers to the adoption of smart agricultural technologies. For example, Dibern and his colleagues examined the main drivers and barriers to the adoption of digital agricultural technologies in their study (Dibbern *et al*., 2024). The aim of the study by Khaspuria *et al.* (2024) was to conduct a comprehensive examination of the adoption of precision agriculture technologies among farmers. The aim of the study by Nandini and Venkataramana, (2024) was to investigate the limitations of adopting smart agricultural technologies. In addition, Mbanasor *et al.* (2024) examined the smart agricultural practices adopted by farmers. The main objective of the study by Shani *et al*. (2024) was to identify the determinants of the adoption of smart agricultural technologies. Bahari *et al.* (2024) aimed to examine the factors influencing the adoption of Internet of Things (IoT) technology in smart agriculture. The objective of the study by Li *et al.* (2023) was to investigate the behavioral adoption mechanism of smart agricultural technologies. The main objective of the study by Serote *et al*. (2023) was to examine the barriers to the adoption of smart irrigation technologies for sustainable crop productivity. In addition, Mhlanga and Ndhlovu, (2023) sought to examine the challenges and complexities associated with the adoption of digital technologies in the agricultural sector. On the other hand, regarding the second aspect of the study's novelty, it can be stated that a review of the theoretical literature indicates that previous studies have rarely examined the effect of adopting smart agricultural technologies on workforce, economic, and environmental outcomes with the moderating role of government policies and regulations. Instead, most studies have mainly focused on the relationship between the adoption of smart agricultural technologies and workforce, economic, and environmental outcomes; For example, Fiawoo and colleagues sought to examine the adoption of smart agricultural technologies and their impact on farmers' performance and income (Fiawoo *et al*., 2024). Jabbari and colleagues, in their study, examined the effect of farmers' perceptions and adoption of smart technologies on crop health and yield prediction (Jabbari *et al*., 2023). Nansky and colleagues, in their study, aimed to examine the impact of smart agricultural technologies on rice production in Japan (Nanseki *et al*., 2023). Yamowa and Kaba, in their study, sought to examine the impact of integrating smart agricultural technology adoption skills and agricultural business management skills on improving the livelihoods of women farmers (Yamoah & Kaba, 2024). Finally, the aim of the study by Zolfaghar and colleagues was to examine the relationship between the use of smart agricultural technologies and the improvement of resource productivity (Zulfikhar *et al*., 2024).

The adoption of smart agricultural technologies is essential for transforming traditional farming practices, overcoming the various changes and transformations in modern agriculture, and paving the way for a more sustainable and efficient future in the agricultural sector. In the present study, the consequences of adopting smart agriculture technologies are examined with the moderating role of government policies and regulations among managers, specialists, and experts in the field of smart agriculture in Tehran and Alborz provinces. Given the above explanations, the main research question can be formulated as follows: Does the adoption of smart agriculture technologies have a significant effect on workforce, economic, and environmental outcomes, with government policies and regulations playing a moderating role? Conducting the present study in the field of smart agriculture in Tehran and Alborz provinces can facilitate farmers' livelihoods, accelerate the country's economic growth, and consequently lead to a reduction in environmental impacts. On the other hand, providing appropriate programs, considering financial incentives, and avoiding the implementation of overly strict policies by the government play an effective role in the adoption of smart agricultural technologies and their resulting outcomes.

Background

Smart agriculture and digital agriculture have emerged as modern strategies aimed at transforming agriculture into a sustainable and productive industry (Otieno, 2023). Smart agriculture, through a precise approach based on the efficient utilization of resources—aligned with environmental considerations—can support sustainable agriculture. In this framework, smart agriculture typically refers to a set of electronic platforms, hardware, and software utilized for collecting, transmitting, and leveraging farm data. These data can include information regarding soil nutrient status, moisture, atmospheric conditions, and other indicators related to the cultivation environment, and can be connected to the system through technological devices such as mobile phones, tablets, and sensor systems. In other words, smart agriculture relies on the synergy between hardware and software layers, linking data and decision-making tools to optimize processes, ensure efficient resource use, increase agricultural land productivity, and improve water consumption management (Putri & Zainuddin, 2024). In other definitions, digital agriculture is described as an agricultural management system that utilizes modern technologies to achieve optimal production in accordance with resource constraints (Hashim *et al.*, 2024; Alumfareh *et al.*, 2024; Von Guionneau, 2024). Also, digital agriculture can be considered the result of integrating various smart technologies that provide the basis for informed decision-making as well as process automation in the field of agriculture (Mutlaq *et al.*, 2022). Ultimately, this approach also creates the capacity to carry out automated operations with minimal human intervention (Hashim *et al.*, 2024). Accordingly, some of the key and prominent technologies in the field of smart agriculture are introduced (Otieno, 2023). These technologies include (Kernecker *et al.*, 2020; Balafoutis *et al.*, 2020; Otieno, 2023):

IoT

This technology forms the backbone of smart farming. By connecting physical devices and sensors to the internet, it enables accurate data collection and remote monitoring (Balafoutis *et al.*, 2020; Hussien *et al.*, 2023). In fact, it collects real-time data on soil moisture, temperature, plant growth, crop health, and other environmental factors, so that farmers can make better data-driven decisions and optimize resource allocation (Otieno, 2023).

Remote Sensing Technology

Remote sensing technologies, such as unmanned aerial vehicles (drones), provide valuable insights into agricultural fields and their crops (Otieno, 2023). A drone, after receiving the initial information, flies along the optimal path and begins performing its tasks such as irrigation, spraying, or even collecting data and capturing images of the agricultural field (Balafoutis *et al.*, 2020; Otieno, 2023). In addition, other technologies such as hyperspectral imaging and multispectral cameras collect high‑resolution images and multispectral data (Otieno, 2023).

Big Data Analytics Technology

The ability to process and analyze large volumes of data is crucial in smart agriculture (Balafoutis *et al.*, 2020). These technologies are used to analyze big data related to weather, soil, and historical crop records (Otieno, 2023). By analyzing these data, farmers can enhance their crop performance (Otieno, 2023).

Robotics and Automation

Autonomous robots and drones equipped with sensors and cameras can perform tasks such as seeding, spraying, and harvesting with high precision and efficiency (Aslan *et al.*, 2022). The deployment of robots in agricultural fields can identify weeds, pests, and nutrient deficiency spots, and subsequently monitor yield, crop quality, and other applications (Otieno, 2023; Mesías-Ruiz *et al.*, 2023). It is noteworthy that the robotic tractor is one of the best‑known robots, capable of operating automatically or without a human operator to perform tillage (Nanseki & Chomei, 2023).

Cloud Computing and Edge Computing

Cloud computing enables the storage, processing, and analysis of agricultural data on remote servers, facilitating scalability and accessibility (Emmi *et al.*, 2023). On the other hand, edge computing brings computational capabilities closer to the devices that generate the data and to the farmers who need it, thereby accelerating real-time decision-making at the field level. Therefore, cloud computing and edge computing support the integration of data from various sources and enable efficient data analysis (Otieno, 2023).

Artificial Intelligence

AI can assist farmers from soil preparation for planting to harvesting through robots and computer engines. In other words, artificial intelligence has considerable potential to enhance the sustainability of the agricultural industry through various applications. For example, it can help identify the optimal timing for harvesting fruits and vegetables, reduce waste, and monitor the health of soil and crops (Mana *et al.*, 2024).

It is important to note that the aforementioned technologies are continuously evolving and becoming more sophisticated. As these technologies continue to advance, farmers can use them to improve productivity, conserve resources, minimize environmental impacts, and contribute to global food security in a rapidly changing and evolving world (Otieno, 2023).

In connection with the expansion of the research hypotheses, it can be argued that the implementation of smart technologies in agriculture is vital to support the advancement of this sector (Nugroho & Aliwarga, 2019). Balafoutis *et al.* (2020)believe that the adoption of smart farming technologies can facilitate agricultural practices, such as farmer stress, farmer workload, and working hours, in addition to work-related injuries. It should be noted that even if it is shown that farmers' stress is significantly reduced, the actual use of a smart agricultural technology can still cause considerable stress due to the need for information processing and technology calibration, as well as when the technologies fail. Of course, stress levels vary across different types of smart farming technologies. Guidance technologies, which have been efficient for years, reduce stress more than variable rate technologies (VRT) that require precise and continuous calibration for proper performance compared to conventional uniform applications. Moreover, the adoption of smart farming technologies reduces farmers' workload and makes life easier for them (Balafoutis *et al.*, 2020). If implemented using modern and efficient technologies, smart farming can make the cultivation process more effective, increase production, and ultimately improve farmers' well-being. In other words, by adopting smart farming technologies, farmers can overcome various challenges in agriculture and improve their overall well-being (Basir *et al.*, 2024). Furthermore, the digitalization of agriculture makes production-related tasks possible at lower cost and in a shorter time, and it transforms farmers' performance (Munnisunker *et al.*, 2022; Javaid *et al.*, 2023).

The digitalization of activities and relationships can introduce new risks to occupational health and safety, such as increased mental workload and the blurring of personal and professional boundaries. While these significant technical advancements may lead individuals—particularly the elderly—to doubt their knowledge and even place them in situations where they feel incapable, resulting in substantial personal instability, learning new technologies or methods through training can be challenging (Munnisunker *et al.*, 2022; Javaid *et al.*, 2023). Good change management involves anticipating psychological risks (such as feelings of dependence, loss of autonomy and identity, and additional mental workload) as well as physical risks resulting from robot malfunction. This approach allows the project to be implemented without causing significant disruption to work settings, tasks, or responsibilities (Mana *et al*., 2024). Therefore, although the adoption of smart farming technologies in agriculture may create new concerns regarding occupational or work-related risks, it can protect farmers from the effects of changes in the workforce force (Munnisunker *et al*., 2022; Javaid *et al*., 2023).

The findings of Yamoah and Kaba, (2024) indicate that social outcomes are among the key consequences of adopting smart farming technologies. The results of Nanseki (2022) study indicated the positive impact of smart farming technologies on workforce savings. Mamilianti (2020) research confirmed that the use of technology can shape positive farmer behavior; therefore, in line with the literature, the first research hypothesis is proposed.

$\boldsymbol{H_1}$: The adoption of smart farming technologies has an effect on workforce -related outcomes.

Smart farming technologies become prominent when it is believed that their economic benefits for farmers are significant. The use of smart farming technologies increases productivity, income, and energy optimization (Balafoutis *et al.*, 2020). Other economic aspects of smart farming technology adoption include the reduction of input costs such as seeds, fertilizers, pesticides, energy, and irrigation, as well as the decrease in variable costs such as raw materials, packaging, and workforce (Madushanki *et al.*, 2019). Furthermore, improved product quality, such as being healthy, clean, pest-free, fresh in appearance, with natural and sufficient physiological and morphological growth, ripeness, firmness, free from spoilage affecting edibility, and the absence of defects, are other key outcomes of adopting smart farming technologies (Balafoutis *et al.*, 2020). Smart farming not only provides numerous economic benefits for farmers, but also contributes to the growth of a country's economy (gross domestic product) (Otitoju *et al.*, 2023). The application of Internet of Things technology in the agricultural sector has numerous advantages. It allows producers (farmers) to increase their productivity and produce more by saving resources (e.g., water) (easy resource management) (Ragaveena *et al.*, 2021; Cihan, 2023). It enables the rapid detection of crop diseases or pests and the implementation of necessary actions (Javaid *et al.*, 2023). In general, Internet of Things technology allows farmers to make better decisions through precise data analysis (Cihan, 2023).

Kasimati *et al.* (2024) in their study, concluded that the adoption of smart farming technologies is effective in improving product quality and increasing economic growth. The results of the study by Yamoah and Kaba, (2024) indicate that economic outcomes are one of the key consequences of adopting smart farming technologies. The results of the study by Nanseki and Chomei, (2023) showed that smart farming technologies have a significant impact on economic performance. The results of the study by Pal *et al*. (2022) confirmed that smart farming technologies can create positive economic outcomes; therefore, based on the explanations provided, the second research hypothesis is stated.

$\boldsymbol{H_2}$ **:** The adoption of smart farming technologies has a positive and significant effect on economic outcomes.

There is now a clear understanding of how smart farming technologies can provide a solution to environmental problems by reducing human intervention through automation (Ena & Huib, 2023). Smart farming technologies can help farmers produce crops more efficiently (Kernecker *et al.*, 2020) and protect the environment and natural resources (Paul *et al*., 2021). The reduction in the use of fertilizers, pesticides, irrigation water, and greenhouse gas emissions is associated with the environmental outcomes of adopting smart farming technologies (Balafoutis *et al*., 2020). By using these technologies, natural resources such as water, soil, and energy can be utilized more efficiently, their consumption can be reduced, and farmers can also be enabled to operate in an environmentally compatible manner (Cihan, 2023). Smart farming technologies, such as Internet of Things (IoT)-based technologies, provide promising solutions for the precise management of resources (Zulfikhar et al., 2024). Internet of Things (IoT) technology can be applied in various areas of agriculture, such as soil management, crop growth, water management, product tracking, and supply chain management. IoT-based sensors enable real-time monitoring of soil moisture levels (Singh *et al.*, 2023) and enhance the overall efficiency of water use in agriculture (Zulfikhar *et al.*, 2024). By employing this technology, crop producers can improve the health and quality of their products and provide consumers with healthier food products. Overall, Internet of Things (IoT) technology offers numerous benefits in the agricultural sector, such as improving productivity, enabling the sustainable use of natural resources, and enhancing product quality (Cihan, 2023). Furthermore, precision agriculture technologies contribute to the efficient use of nutrients and crop management, potentially reducing the environmental footprint of agricultural activities (Singh *et al.*, 2023). The integration of precision agriculture technologies leads to a significant reduction in water consumption while simultaneously increasing crop yield (Zulfikhar *et al.*, 2024). By using these technologies, farmers can make informed decisions regarding pest control, irrigation, and fertilization, which leads to increased efficiency, reduced waste, and higher crop yields (Pal & Joshi, 2023). On the other hand, Loures *et al.* (2020) examined the impact of using remote sensing techniques on small farms. They concluded that the efficient use of these technologies improves crop productivity and farm profitability, and promotes sustainable agriculture both ecologically and economically (Otieno, 2023). Overall, the use of smart farming technologies can help address critical concerns such as water scarcity, energy consumption, and land use, leading to more sustainable agricultural practices (Pal & Joshi, 2023). In other words, smart farming enables farmers to achieve better performance by optimizing farm management, reducing the use of fertilizers, pesticides, and water, and contributing to improved and more sustainable outcomes (Otieno, 2023).

The adoption of smart farming technologies can lead to a reduction in greenhouse gas emissions (nitrous oxide, methane, and carbon dioxide), thereby positively influencing climate change mitigation and reducing global warming potential. It can contribute to biodiversity by optimizing inputs (such as variable-rate fertilization or pesticide application) and reducing spray drift (Balafoutis *et al.*, 2020). In addition, the adoption of these technologies can reduce the impacts of weed, pest, and disease growth on farmland and crops (Balafoutis *et al.*, 2020; Lieder & Schröter-Schlaack, 2021). Moreover, the use of small-scale robots for planting can prevent environmental damage caused by heavy machinery and help preserve soil sustainability (Lieder & Schröter-Schlaack, 2021). It is noteworthy that the findings of Yamoah and Kaba, (2024) indicate that environmental outcomes are among the key consequences of adopting smart farming technologies. Furthermore, the study by Kasimati *et al.* (2024) revealed that the adoption of smart farming technologies is effective in reducing environmental impacts; therefore, based on the explanations provided, the third research hypothesis is formulated.

$\boldsymbol{H_3}$**:** The adoption of smart farming technologies has a positive and significant effect on environmental outcomes.

Government support plays an important role in facilitating the adoption of smart farming technologies (Bahari *et al.*, 2024). In other words, policies and initiatives that promote the use of smart farming technologies can have a positive impact on farmers' decisions to adopt these technologies (Sun *et al.*, 2021; Everest, 2021). Farmers' perception of active government support plays a significant role in their decision to adopt smart farming technologies (Jabbari *et al.*, 2023; Meng *et al.*, 2023). When farmers perceive that the government actively supports the adoption and implementation of smart technologies in agriculture, they are more likely to embrace these technologies. Government support can include financial incentives such as subsidies, policy frameworks, and support programs (Sun *et al.*, 2021; Everest, 2021; Singh *et al.*, 2021; Meng *et al.*, 2023). Government support creates a conducive environment for farmers, builds their trust, and reduces potential barriers to adoption. In this way, government support reflects its commitment to modernizing the agricultural sector and promoting sustainable farming practices (Meng *et al.*, 2023). Accordingly, the availability of accurate information and educational resources is important for the successful adoption of smart farming technologies. Farmers need precise and up-to-date information about smart farming technologies and their efficient implementation. Training programs and workshops can enhance farmers' understanding of these technologies (Sun *et al.*, 2021; Everest, 2021). Studies have shown that farmers who have access to comprehensive information and training programs are more likely to adopt smart technologies in their agricultural activities and use them effectively. Available information channels, such as agricultural extension services, workshops, seminars, and online resources, help farmers understand the benefits and outcomes of smart farming technologies (Haque *et al.*, 2021; Li *et al.*, 2023). Farmers must have access to training programs to acquire the skills and knowledge necessary for efficient and effective use of the technologies (Singh *et al.*, 2021). Therefore, reducing training costs and equipping farmers with essential skills through government-supported programs can significantly increase the use of smart farming technologies, thereby improving their effectiveness and efficiency (He *et al.*, 2023).

On the other hand, imposing taxes or levies on certain smart farming technologies significantly increases the cost of access to these technologies (Chen *et al.*, 2023). Although countries like China and the United States have the potential and capability to produce these technologies and benefit from cost reductions and competitive prices, some countries (mostly developing ones) import and then assemble these technologies, which leads to increased costs due to the payment of tariffs. To increase affordability and support domestic production, it is necessary to invest in the local manufacturing of smart farming technologies (Makam *et al.*, 2024) or to provide financial incentives such as subsidies, tax exemptions, and grants for importing these technologies (Jiang & Xu, 2023).

Islam *et al.* (2024) found in their study that the lack of government support, the implementation of strict policies, and the absence of appropriate government programs are among the barriers to the adoption of smart farming technologies. The results of the study by Jaroenwanit *et al.* (2023) indicate that government support had the greatest influence on smart agricultural decision-making in risk management. Azam and Shaheen, (2018) conducted a government-supported study in which they examined the factors influencing farmers' decision-making in smart farming. Their findings showed that marketing factors and government policies are the most important elements in persuading farmers to adopt smart farming practices, regardless of their level of education. In fact, the results of this study indicate that the adoption of smart farming is unlikely to be achieved without government support. Furthermore, the results of the study by Aryal *et al.* (2018) confirmed that government support is an important factor in the adoption of smart farming. Amondo and Simtowe, (2018) found that farmers who rejected smart farming technology discontinued its adoption and use for a period of time and eventually stopped using it altogether. This was mainly due to the lack of serious and continuous government promotion; therefore, based on the explanations provided, the fourth and fifth hypotheses and the research are presented.

$\boldsymbol{H_4}$**:** Government policies and regulations positively moderate the relationship between the adoption of smart farming technologies and workforce -related outcomes.

$\boldsymbol{H_5}$**:** Government policies and regulations positively moderate the relationship between the adoption of smart farming technologies and economic outcomes.

$\boldsymbol{H_6}$**:** Government policies and regulations positively moderate the relationship between the adoption of smart farming technologies and environmental outcomes.

Based on the explanations provided, the conceptual model of the study is presented in Fig. 1.

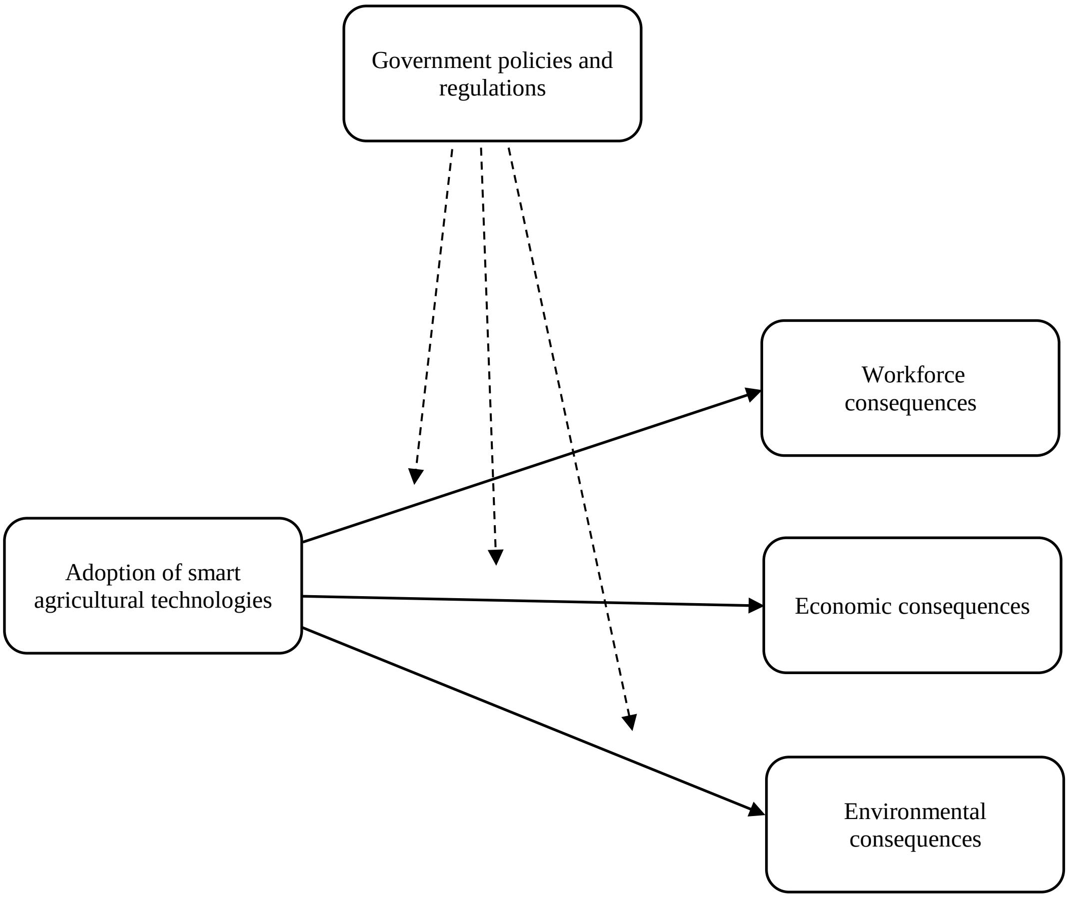

Figure 1- Conceptual model of the study
References (Islam *et al*., 2024; Zulfikhar *et al*., 2024; Basir *et al*., 2024; Bahari *et al*., 2024; Cihan, 2023; Jabbari *et al*., 2023; Lieder & Schröter-Schlaack, 2021; Balafoutis *et al*., 2020; Kernecker *et al*., 2020**)**

Methodology

Population and Sample of the Study

The target population of this study consists of managers, specialists, and experts in the field of smart agriculture in Tehran and Alborz provinces, Iran. This study is applied in terms of its purpose and descriptive- survey in terms of its nature and methodology. The sampling method is non-probability convenience sampling. One of the methods for determining the minimum sample size is the ratio of the number of sample members to the number of items in the research model, known as the N:q theory. The minimum recommended ratio proposed by Jackson (2003) is 10:1 (Norouzi *et al*., 2024). Accordingly, considering the number of questionnaire items (27 questions), the sample size was estimated to be 270 participants. However, to ensure adequacy, a larger sample—15 times the number of items, equivalent to 405 questionnaires—was distributed in person. Ultimately, 350 completed questionnaires were collected and analyzed.

Data Collection Instrument

In the present study, a questionnaire has been used as the data collection instrument. The instrument was designed and structured based on two sections: demographic data and specialized questions. The first section includes questions regarding the respondents' general characteristics, such as gender, marital status, age, education level, and work experience, while the information in the second section is presented in Table 1. Additionally, the scale used in the questionnaire is a five-point Likert scale consisting of: strongly disagree, disagree, neutral, agree, and strongly agree.

Table 1- Composition of the questionnaire's specialized questions

Row	Variables	Number of questions	References
1	Acceptance of Smart Agriculture Technologies	4	Hosseininia *et al*., 2021
2	Government Policies and Regulations	4	Bahari *et al*., 2024; Islam *et al*., 2024
3	workforce Force Consequences	6	
4	Economic Consequences	6	Balafoutis *et al*., 2020; Kernecker *et al*., 2020
5	Environmental Consequences	7	

Statistical Analysis Methods

The collected data were analyzed using structural equation modeling (SEM) with a partial least squares (PLS) approach, employing the Smart‐PLS 3 software. Since the partial least squares technique is less sensitive to sample size and does not require data normality, this software was selected.

Descriptive Analysis

Regarding the results of the respondents' demographic characteristics, which include managers, specialists, and experts in the field of agriculture, it can be explained that 21.6% of the respondents are female and 78.4% are male. A total of 27.2% of the respondents are single, and 72.8% are married. The largest proportion of respondents, equivalent to 45.2%, are between 41 and 50 years old, while the smallest proportion, about 9.6%, are between 20 and 30 years old. Regarding educational status, the largest proportion of respondents, equivalent to 55.2%, hold doctoral degrees, while the smallest proportion, about 1.2%, have a high‐school diploma or lower. Finally, the largest proportion of respondents, equivalent to 27.2%, have 6 to 10 years of work experience, while the smallest proportion, about 12.8%, have less than 5 years of work experience.

Inferential Analysis

For the statistical analysis, structural equation modeling was used, employing the measurement model followed by the structural model. The measurement model represents the manner in which latent and observed variables are related, while the structural model indicates the relationships between latent or underlying variables (Asgarnezhad Nouri *et al*., 2022). In the present study, several validity criteria—including construct validity, convergent validity, and discriminant validity—along with two reliability coefficients, namely composite reliability and Cronbach's alpha, were used to assess the fit of the measurement model. Asgarnezhad Nouri *et al.* (2022) believe that construct validity indicates the degree of consistency between the results obtained from applying the measurement instruments and the theories upon which the test is designed. In addition, discriminant validity is used to examine the extent to which the items of one factor differ from the items of other factors. Convergent validity is also employed to assess the degree of correlation between each factor and its own corresponding items (Reshadatnia *et al*., 2020).

Table 2– Results of construct validity (Confirmatory factor analysis) and reliability.

Variable	Item	Factor loading	Cronbach's Alpha	Composite reliability
Acceptance of smart agriculture technologies	1. I accept the use of smart agriculture technologies in the near future.	0.814	0.846	0.897
	2. I recommend the use of smart agriculture technologies to others.	0.825		
	3. I accept continuing the use of smart agriculture technologies.	0.849		

Government policies and regulations	4. I accept repeated use of smart agriculture technologies.	0.821	0.865	0.908
	5. Promoting smart agriculture requires sufficient government support, including providing adequate internet infrastructure in rural areas, launching training programs for technicians, educating farmers, offering easy loan facilities for start‐ups and farmers, supplying auxiliary equipment, and other related support.	0.858		
	6. The government provides various forms of support to agricultural organizations to introduce smart agriculture technologies.	0.832		
	7. The government promotes smart agriculture by disseminating successful case studies and providing technical training.	0.842		
	8. The government supports various agricultural information projects for agricultural organizations.	0.842		
Workforce force consequences	9. Adoption of smart agriculture technologies can reduce work time through applications such as robotics, auto guidance, and remote operations.	0.597	0.876	0.908
	10. Adoption of smart agriculture technologies can reduce farmers' stress through better resource optimization and operational planning.	0.834		
	11. Adoption of smart agriculture technologies can decrease heavy workforce by using automation and robotic technologies for demanding field operations.	0.852		
	12. Adoption of smart agriculture technologies (equipment such as automation and robotics) can reduce farmers' injuries, for example, automatic coupling or automatic filling of sprayers.	0.804		
	13. Adoption of smart agriculture technologies can decrease occupational physical or psychological harm through providing advanced sensors for active and passive operations.	0.820		
Economic consequences	14. Adoption of smart agriculture technologies can provide better information for farmers' decision-making.	0.808	0.862	0.896
	15. Adoption of smart agriculture technologies can increase productivity (efficiency and effectiveness).	0.803		
	16. Adoption of smart agriculture technologies can improve product quality (e.g., healthiness, cleanliness, pest‐free condition, fresh appearance, adequate physiological and morphological growth, ripeness, firmness, absence of decay affecting edibility, and lack of defects).	0.809		
	17. Adoption of smart agriculture technologies can reduce input costs (e.g., seed, fertilizer, pesticides, fuel, and irrigation) and variable costs (e.g., raw materials, packaging, and workforce).	0.777		
	18. Adoption of smart agriculture technologies can help increase income through optimizing production and product quality.	0.768		
	19. Adoption of smart agriculture technologies can contribute to better product preservation, selective harvesting, and reducing product loss or waste (e.g., fruits with spots, pest marks, or irregular shapes caused by abnormal growth).	0.731		
	20. Adoption of smart agriculture technologies can reduce energy consumption and related costs (e.g., tractor use).	0.716		
Environmental consequences	21. Adoption of smart agriculture technology can lead to lower greenhouse gas emissions (nitrous oxide, methane, and carbon dioxide), positively influencing climate change and global warming potential.	0.854	0.895	0.918
	22. Optimized crop production using smart agriculture technologies can preserve biodiversity and soil sustainability or contribute to maintaining soil health.	0.798		
	23. Adoption of smart agriculture technologies can support biodiversity by optimizing inputs (variable‐rate fertilization or pesticide application) and reducing spray drift.	0.803		

24. Adoption of smart agriculture technologies can reduce pesticide use and fertilizer consumption in agricultural production.	0.816
25. Adoption of smart agriculture technologies can reduce pesticide residues.	0.797
26. Optimizing water use through the application of smart agriculture technologies helps conserve water resources and reduce excessive pumping.	0.743
27. Adoption of smart agriculture technologies can reduce the effects of weed growth, pests, and diseases in the field.	0.704

On the other hand, composite reliability and Cronbach's alpha coefficient indicate the internal consistency of the items that measure the same construct (Mola Ghalghachi & Bashir Khodaparasti, 2023).

Measurement Model

To evaluate the fit of the measurement model, two indices—reliability and validity—were used, as presented in Table 2.

The reliability of the research questionnaire was assessed using factor loadings (confirmatory factor analysis), Cronbach's alpha coefficient, and composite reliability. The desirable value for factor loadings, Cronbach's alpha, and composite reliability is preferably above 0.7 (Mola Ghalghachi & Bashir Khodaparasti, 2023). Therefore, the values presented in Table 2 indicate highly desirable factor loadings—namely, above 0.7 for each observed variable. Moreover, the results for Cronbach's alpha and composite reliability also demonstrate the satisfactory reliability of the variables.

On the other hand, the results of convergent and discriminant validity are presented in Table 3. It should be noted that in the present study, the Fornell–Larcker criterion was used to assess discriminant validity.

Table 3- Assessment of Convergent and Discriminant Validity of the Measurement Model

Variable	Average Variance Extracted (AVE)	Fornell–Larcker 1	2	3	4	5
1. Government Policies and Regulations	0.711	0.843				
2. Acceptance of Smart Agriculture Technologies	0.685	0.446	0.827			
3. Workforce Force Consequences	0.590	0.498	0.470	0.768		
4. Economic Consequences	0.615	0.623	0.623	0.709	0.784	
5. Environmental Consequences	0.625	0.545	0.513	0.579	0.730	0/790

Based on Table 3, the Average Variance Extracted (AVE) criterion was used to assess convergent validity. According to Mola Ghalghachi and Bashir Khodaparasti, (2023), this criterion reflects the extent to which a construct correlates with its own indicators, and they further note that the greater this correlation is, the better the model fit will be. Therefore, the point that "the desirable value for the Average Variance Extracted (AVE) criterion should be above 0.50" is satisfied in Table 3. Furthermore, Asgarnezhad Nouri *et al*. (2022) believe that the Fornell–Larcker criterion represents the extent to which a construct is more strongly related to its own indicators compared to its relationships with other constructs. The results are interpreted such that if the square root of the Average Variance Extracted (AVE) for the latent variables—shown in the cells along the main diagonal of the matrix—is greater than the correlation values in the cells below and to the right of the diagonal, then discriminant validity is considered satisfactory (Mola Ghalghachi & Bashir Khodaparasti, 2023). Therefore, Table 3 indicates that the variables exhibit acceptable discriminant validity. Structural model.

It is worth noting that the output of the conceptual model of the research can be presented in Fig. 2.

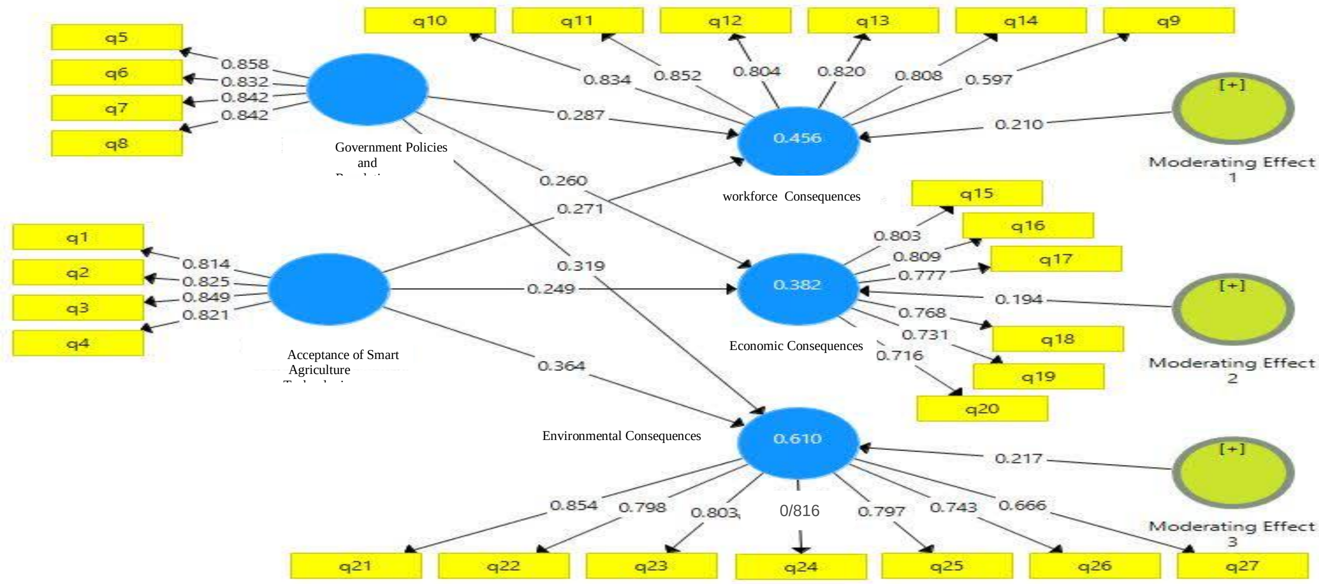

Figure 2- Model output including path coefficients, determination coefficients (R^2), and factor loadings

Regarding the analysis of Fig. 2, it can be stated that since the path coefficients, or beta coefficients, represent the amount of explanation, strength, and direction of the effect between two latent variables—and their values range between -1 and +1—there is a linear relationship between the latent variables of the study according to Fig. 2. In Fig. 2, the numbers between the observed and latent variables (confirmatory factor analysis) represent the factor loadings. Additionally, the numbers between the latent variables indicate the path coefficients, and the numbers inside the circles represent the determination coefficients (R^2) of the endogenous latent variables. On the other hand, Fig. 3 shows the research model output along with the t-values.

After obtaining the conceptual model output along with the path coefficients, the research model output including the significance of t-values is generated to examine the significance of the paths. The t-value significance numbers serve as a criterion for assessing the relationships between variables in the structural model. If these values exceed 1.96, the validity of the relationships between constructs—and consequently the confirmation of the research hypotheses—is supported at various confidence levels. Therefore, Fig. 3 indicates the confirmation of the model's paths.

It should be noted that, according to the software output, the results of the research hypotheses are explained in Table 4.

Based on Table 4, all hypotheses are supported because the path coefficients are positive and the t-values are greater than 1.96.

The values related to the model fit indices are presented in Table 5.

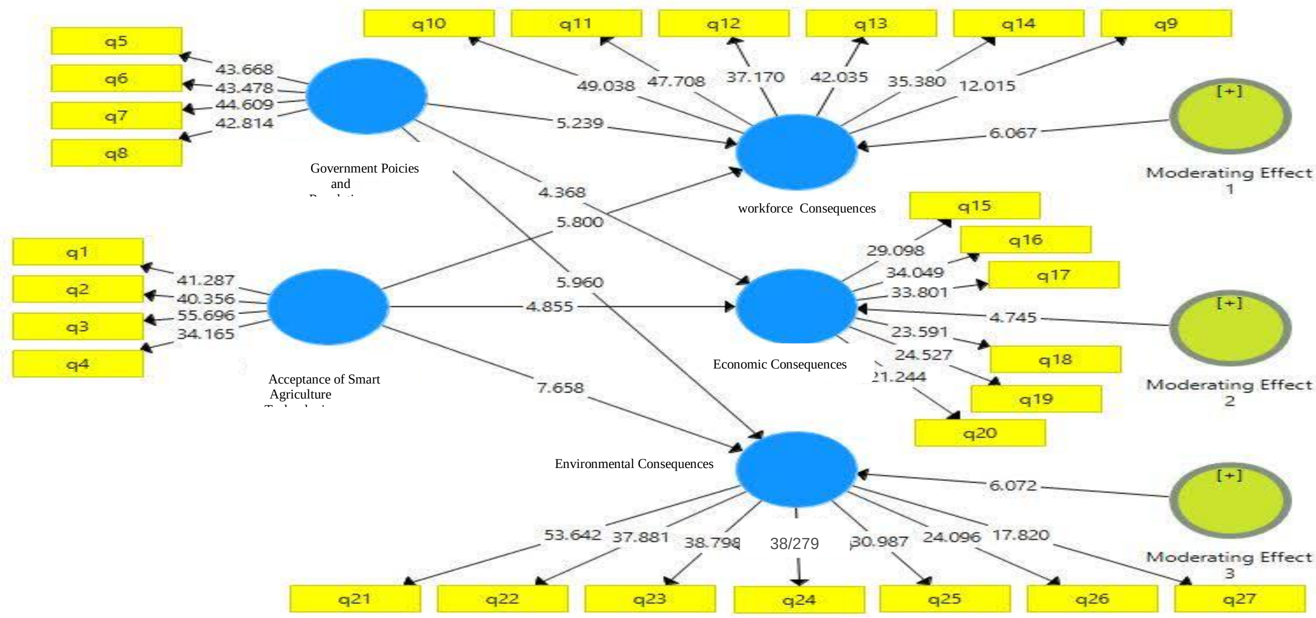

Figure 3- Model output including t-statistics significance coefficients

Table 4- Results of the hypotheses

Hypothesis	Path coefficient	t-value	Result
1. Acceptance of smart agriculture technologies affects workforce force Consequences.	0.271	5.800	Supported
2. Acceptance of smart agriculture technologies has a positive and significant effect on economic Consequences.	0.249	4.855	Supported
3. Acceptance of smart agriculture technologies has a positive and significant effect on environmental Consequences.	0.364	7.658	Supported
4. Government policies and regulations positively moderate the relationship between acceptance of smart agriculture technologies and workforce force Consequences.	0.287	5.239	Supported
5. Government policies and regulations positively moderate the relationship between acceptance of smart agriculture technologies and economic Consequences.	0.260	4.368	Supported
6. Government policies and regulations positively moderate the relationship between acceptance of smart agriculture technologies and environmental Consequences.	0.319	5.960	Supported

Table 5- Model fit results

Variable	Coefficient of determination (R^2)	Redundancy index (Q^2)	Communality index	Goodness of fit (GOF)
Government Policies and Regulations	–	–	0.711	0.558
Acceptance of Smart Agriculture Technologies	–	–	0.685	
Workforce Force Consequences	0.456	0.253	0.590	
Economic Consequences	0.382	0.198	0.615	
Environmental Consequences	0.610	0.343	0.625	

According to Table 5, the «coefficient of determination» index is used to connect the measurement model and the structural model in structural equation modeling. This criterion indicates the effect that an exogenous variable has on an endogenous variable. The values 0.19, 0.33, and 0.67 are defined as the thresholds for weak, moderate, and strong levels of the coefficient of determination, respectively. Additionally, the redundancy index determines the predictive power of the model. For the strength of the model's predictive power regarding endogenous constructs, the values 0.02, 0.15, and 0.35 can be considered as thresholds for weak, moderate, and strong predictive power, respectively

(Deljo *et al.*, 2021). Therefore, Table 5 shows favorable results for these criteria. To evaluate the quality of measurement models in the PLS method, an index called the "communality index" can be used. This criterion indicates how much of the variability of the indicators (questions) is explained by their related construct. Positive values of this index represent an appropriate and acceptable quality of the measurement model (Deljo *et al.*, 2021). Therefore, Table 5 presents the output of this criterion from the Smart-PLS software, indicating the appropriate quality of the measurement model. It is worth noting that, in this study, the Goodness of Fit (GOF) index was used to assess the overall model fit. Three values, namely 0.01, 0.25, and 0.36, are introduced as weak, moderate, and strong levels for the GOF index, respectively. The higher the value of this index, the better the overall fit of the model can be considered. Therefore, Table 5 shows the values of this index, and the result indicates the high strength of the model with a value of 0.558.

Discussion and Analysis

The results of the examination of the first research hypothesis showed that the adoption of smart farming technologies has a positive and significant effect on workforce-related outcomes. Regarding the confirmation of the aforementioned hypothesis, it can be stated that the adoption of smart farming technologies is an important driver of workforce-related outcomes; in other words, the adoption of smart farming technologies can facilitate agricultural activities such as farmers' stress, workload, and working hours, thereby improving farmers' well-being. This finding is consistent with the results of studies by, among others, Yamoah & Kaba, 2024; Nanseki, 2022; Mamilianti, 2020. On the other hand, based on the test of the second research hypothesis, it was determined that there is a positive relationship between the adoption of smart farming technologies and economic outcomes. In fact, the adoption of smart farming technologies directly affects economic outcomes. Accordingly, the adoption of smart farming technologies provides multiple economic benefits for both farmers and the national economy (GDP). The use of smart farming technologies increases productivity, income, and product quality. In other words, these technologies make agricultural activities more efficient and effective, allowing producers (farmers) to increase productivity and produce more high-quality products using fewer resources. This finding is consistent with the results of studies such as Kasimati *et al*., 2024; Yamoah & Kaba, 2024; Nanseki & Chomei, 2023; Pal *et al*., 2022. It is worth mentioning that the confirmation of the third research hypothesis indicates that the positive effect of adopting smart farming technologies extends to environmental outcomes. Accordingly, smart farming technologies can help farmers produce crops more efficiently while protecting the environment and natural resources. Reducing the use of fertilizers, pesticides, irrigation water, and greenhouse gas emissions are attributed to the environmental outcomes of adopting smart farming technologies. Therefore, by using these technologies, natural resources such as water, soil, and energy can be used optimally, enabling farmers to operate in an environmentally sustainable manner. This finding is consistent with the results of studies such as Yamoah & Kaba, 2024; Kasimati *et al*., 2024. Furthermore, the data analysis and interpretation regarding the confirmation of hypotheses four, five, and six of the study highlight the moderating role of government policies and regulations in the relationship between the adoption of smart farming technologies and workforce, economic, and environmental outcomes. Government support plays a crucial role in facilitating the adoption of smart farming technologies. Government support, which includes providing subsidies for inputs such as the procurement of smart farming technologies, offering comprehensive information and appropriate training programs for farmers, as well as imposing low taxes on imported smart farming technologies, can create favorable conditions for the adoption of these technologies and, consequently, their various outcomes. These results are consistent with the findings of studies such as Islam *et al*., 2024; Jaroenwanit *et al*., 2023; Azam & Shaheen, 2018; Aryal *et al*., 2018; Amondo & Simtowe, 2018.

Conclusion

The aim of the present study was to examine the outcomes of adopting smart farming technologies, considering the moderating role of government policies and regulations, among managers, specialists, and experts in the agricultural sector of Tehran and Alborz provinces, Iran. The results of the data analysis showed that the first hypothesis of the study, which stated that the adoption of smart farming technologies has a positive and significant effect on workforce -related outcomes, was supported. Similarly, the first hypothesis has also been confirmed in studies such as Yamoah & Kaba, 2024; Nanseki, 2022; Mamilianti, 2020. The results of the data analysis showed that the second and third hypotheses of the study, which respectively stated that the adoption of smart farming technologies has a positive and significant effect on economic and environmental outcomes, were supported. The second hypothesis has also been confirmed in studies such as Kasimati *et al*., 2024; Yamoah & Kaba, 2024; Nanseki & Chomei, 2023; Pal *et al*., 2022, while the third hypothesis has been supported in studies by Yamoah & Kaba, 2024; Kasimati *et al*., 2024. Furthermore, the fourth, fifth, and sixth hypotheses of the study, which indicate the moderating role of government policies and regulations in the relationship between the adoption of smart farming technologies and workforce, economic, and environmental outcomes, were confirmed. The results of these three hypotheses have also been supported in previous studies such as Islam *et al*., 2024; Jaroenwanit *et al*., 2023; Azam & Shaheen, 2018; Aryal *et al*., 2018; Amondo & Simtowe, 2018.

Managers, specialists, and experts in the agricultural sector play a major role in this field. As climate change occurs—meaning that everything is changing—the production system must adapt accordingly. Therefore, in line with the confirmed positive effects of adopting smart farming technologies on workforce, economic, and environmental outcomes, it is recommended that managers, specialists, and experts in the agricultural sector establish research centers for artificial intelligence and big data and engage in useful activities related to smart farming technologies. In fact, they should facilitate the dissemination of knowledge or new knowledge within the country. They should also develop new models and patterns to ensure that enough food can be supplied for the country in the coming years. They should collect accurate and reliable data by utilizing artificial intelligence technologies in order to develop new models. They should also properly analyze the past so that they can shape the future. It is also recommended to participate in national artificial intelligence events related to the agricultural sector. Therefore, if these actions are implemented, the workforce, economic, and environmental benefits of smart farming technologies can be realized. On the other hand, regarding the confirmation of the moderating role of government policies and regulations in the relationship between the adoption of smart farming technologies and workforce, economic, and environmental outcomes, it is recommended that policymakers provide incentives such as subsidies to facilitate access like smart farming technologies and thereby enhance their affordability. Moreover, by implementing training programs, comprehensive information regarding the use of smart farming technologies should be provided to farmers along with certification; this means that accessible information channels—such as agricultural extension services, workshops, seminars, and online resources—help enhance farmers' understanding of the potential benefits and performance of smart farming technologies.

One of the fundamental limitations of the present study is that the conditions for the use and adoption of smart farming technologies are not the same or similar across all provinces. Therefore, caution should be exercised when generalizing the study's results to other provinces. On the other hand, managers, specialists, and experts in the agricultural sector had sufficient knowledge about the concepts of technology adoption, artificial intelligence, and smart farming; however, due to the novelty of smart farming technologies, they were not sufficiently familiar with the specific concept of smart farming technology adoption. In addition to the limitation, the existing literature on the moderating role of government policies and regulations in the relationship between the adoption of smart farming technologies and workforce, economic, and environmental outcomes was scarce and limited. It should be noted that the researchers' access to domestic studies was very limited, given the new and emerging nature of smart farming technology adoption in the theoretical literature. Finally, the use of a questionnaire for data collection is considered another limitation of the present study, as not all respondents had the same understanding of the questionnaire items, and the researchers had no control over the level of accuracy and motivation of the respondents when answering the questions.

Considering the aforementioned limitations, it is suggested that future researchers examine the research model in companies operating in Iran, such as knowledge-based companies in the field of smart agriculture. Furthermore, a comparative approach could be used to compare the results of different studies, and ultimately to present the resulting managerial and operational recommendations. Additionally, future researchers are advised to thoroughly test and examine the current research model using qualitative methods, such as the grounded theory approach, in active provinces within the agricultural sector.

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مطالعهٔ پیامدهای پذیرش فناوری‌های کشاورزی هوشمند با نقش تعدیلگر سیاست‌ها و مقررات دولتی

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چکیده

بخش کشاورزی یکی از حوزه‌هایی است که فناوری‌های کشاورزی هوشمند در آن کاربرد زیادی دارند. فناوری‌های کشاورزی هوشمند پتانسیل تجزیه وتحلیل داده‌های کشاورزی را در مقیاسی ارائه می‌دهند که قبلاً امکان‌پذیر نبود. پذیرش فناوری‌های کشاورزی هوشمند پتانسیل بهبود بهره‌وری و سودآوری در کشاورزی را دارد و در عین حال پایداری را نیز بهبود می‌بخشد. دستیابی به این پتانسیل نه تنها به پیشرفت تکنولوژی نیاز دارد، بلکه نیازمند درک دقیق پیامدهایی است که پذیرش فناوری‌های کشاورزی هوشمند بر آنها تأثیر می‌گذارد. با توجه به توضیحات مذکور، پراکندگی پژوهش‌های قبلی و نبود نگاه جامع، هدف پژوهش حاضر، مطالعهٔ پیامدهای پذیرش فناوری‌های کشاورزی هوشمند با نقش تعدیلگر سیاست‌ها و مقررات دولتی است. جامعهٔ آماری پژوهش شامل مدیران، کارشناسان و خبرگان حوزهٔ کشاورزی هوشمند در استان تهران و البرز است. یکی از روش‌های تعیین حداقل حجم نمونه، روش نسبت تعداد اعضای نمونه به تعداد سؤالات مدل پژوهش یا نظریهٔ N:q است که حداقل نسبت پیشنهادی توسط جکسون است. بر همین اساس با توجه به تعداد گویه‌های پرسش‌نامه (۲۷ سؤال)، حجم نمونه ۲۷۰ نفر برآورد شد. ابزار گردآوری داده‌ها پرسش‌نامه است. روایی پرسشنامه به‌صورت تشخیصی، هم‌گرا و واگرا و پایایی پرسشنامه نیز با ضریب آلفای کرونباخ و پایایی ترکیبی بررسی شد. آزمون مدل پژوهش براساس روش حداقل مربعات جزئی و به کمک نرم‌افزار Smart - PLS 3 انجام شد. نتایج تجزیه‌وتحلیل داده‌ها نشان داد که پذیرش فناوری‌های کشاورزی هوشمند بر پیامدهای نیروی کار، اقتصادی و زیست‌محیطی تأیر مثبت و معنادار دارد. علاوه بر این، سیاست‌ها و مقررات دولتی در ارتباط بین پذیرش فناوری‌های کشاورزی هوشمند و پیامدهای نیروی کار، اقتصادی و زیست‌محیطی نقش تعدیلگر مثبت دارد.

واژه‌های کلیدی: پذیرش فناوری، پیامدهای اقتصادی، پیامدهای زیست‌محیطی، پیامدهای نیروی کار، کشاورزی هوشمند

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