

The gap between technology and agriculture, barrier identification and potential solution analysis

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Abstract: With the recent developments, emerging technologies like artificial intelligence are being used in our daily tasks to assist us in our jobs, simplifying complex tasks, and even making decisions in specific areas. Agriculture is also touched by these developments and is actually one of the areas where applications in most of the latest technologies are found and benefited from. Surprisingly, different research shows that there is a considerable gap between technology and agricultural practices, even in developed areas, although the technological development in this field is advancing on a daily basis. This paper first gathers general information about agriculture from local farmers in a developing country through questionnaires. We also focus on farmers' opinions about technology in agriculture and what type of barriers they encounter when it comes to implementing it in their daily work. Then, after identifying barriers, we suggest recommendations about the type of technologies that can be used and adapted in the region where questionnaires were conducted in order to find solutions for identified barriers. The solutions include technical implementations with a focus on low cost and usability (user friendly) with the goal to also extend to regions with similar characteristics.

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Keywords: Smart agriculture, barriers, precision agriculture, edge computing, artificial intelligence.

1. INTRODUCTION

The importance of agriculture is re-appearing day by day, especially with the latest developments like pandemics and the highly increasing world population, where people realize how important it is to produce enough food especially when such a crisis appears (UN, n.d.). And, of course, technology is trying to contribute in that direction in order to create practical solutions for such problems. Different approaches are taken in that direction by trying to implement both traditional and state-of-the-art technologies. One of the latest trends in this direction is the application of the Internet of Things (IoT) on agriculture (Friha, et al., 2021) where the main idea is to collect as much as possible data, store that data in the cloud, and processing it to generate different results and reports, and based on these results, make different decisions. IoT is also helping in areas like process automation in agriculture, distance control for different processes, agrochemicals control, etc. which are finding applications more and more each day (Shetty & Smitha, 2021).

Another technological application that is also getting a lot of attention is implementing drones and artificial intelligence (AI) in agriculture. AI is being applied in agriculture in different areas, but mostly the focus is on analyzing complex data from different sensors and images, and as a result, making decisions or at least giving suggestions about specific processes like soil management or disease detection (Shetty & Smitha, 2021). Also, drones are combined with

AI in order to enhance the capturing of images, monitoring of different crops, and dispersing various agrochemicals in crop fields (Mandal, et al., 2022).

All of these developments and applications of technology in agriculture are summarized as precision farming or smart agriculture. However, if there is such a big development toward smart agriculture, why are there still no robots, drones and other high-tech devices implemented practically on a large scale, thus creating a noticeable impact in agriculture? If even developed countries are not implementing these technologies widespreadly, what about less developed countries? Could these technologies also help there or maybe a different approach is needed?

During this paper, we will be focusing on addressing three main questions:

1. While there are novel technologies suitable for use in agriculture, why do farmers adopt these technologies so slowly?
2. What type of barriers are holding farmers back?
3. What type of technologies are more suitable for and can be more easily adapted by farmers based on the barriers they identify?

The first two questions are related to each other and we address them in the state of the art chapter, where we analyze how different researchers approach these questions in different

countries in the world (Long, et al., 2016) (Antwi-Agyei, et al., 2021). We ask the same questions with a questionnaire to local farmers in Kosovo. Based on the results of the questionnaire and our research on the state of the art technology (Chaterji, et al., 2021), we discuss the third question, especially what types of technologies are more adaptable and make future recommendations about specific implementation cases and types of hardware to use in order to overcome the barriers that farmers identify and close the gap between applied technologies and agriculture.

2. STATE OF THE ART

In this chapter, we analyze related work illuminating the barriers of smart technology adaptation in agriculture, in both developed and developing countries, the methods they use to obtain their results, and also the latest technologies used in this field today.

Chaterji and et al. (2021) give a general overview of the state-of-the-art technologies that can be applied or are already applied in the field of agriculture. The authors also state that most new technologies encounter financial barriers as a result of their high prices. Mostly the focus of the paper is on technologies like the Internet of Things (IoT) and Machine Learning (ML) technologies, data processing and analytics, and different type of algorithms applied to these technologies. Oliveira and et al. (2021) also discuss the latest technologies whereas the focus is mostly on mobile robots that are used for different tasks in agriculture. The authors cover a lot of existing robots that perform tasks such as land preparation before planting, planting process, sowing, plant treatment, harvesting, etc. Almost every robot/project in the paper uses one of the latest technologies like Artificial Intelligence, IoT, or machine vision. However, they also remark that most of these projects are still in the research phase and not fully implemented.

Long, et al. (2016) focus and identify key socio-economic barriers in terms of both supply and demand. Qualitative data was collected from key informants of both sides in form of interviews and then processed to create final results. The answers from technology providers show that one of the first coming barriers is convincing customers that state-of-the-art technology is worth it and beneficial for them. Other barriers include lack of knowledge and access to investment, unfriendly regulators, the high price of the final product, and access to customers. On another side, we have demand or technology users (farmers) side of the barriers. The first coming barrier was low awareness and lack of understanding of the developed technologies following high cost, lack of verified impact of technologies, regulatory and policy issues, hard to reach and train farmers, R&D and policies not matching to 'on-the-ground' reality, low consumer demand, and unequal distribution of costs/benefits across supply chains.

(Gandorfer, et al., 2018) address the issue of barriers in developed countries like Germany. Results show that the main factors that keep farmers from implementing new technologies are data protection and incompatibility between different hardware and software. While (Barnesa, et al., 2018) discuss the same issues existing in five countries: Belgium, Germany,

Greece, the Netherlands, and UK. They state that the main barrier to the adaptation of precision agriculture technologies is the high cost which also concludes that bigger farmers tend to adopt these technologies more than smaller farmers.

(Antwi-Agyei, et al., 2021) focus on developing country zones with similar results. Data collected using questionnaires with a focus on the socioeconomic characteristics of responders, climate-smart agricultural practices, and enablers and barriers to implementing them, shows interesting barriers. Farmers stated that pests and diseases increase the cost of farming and as a result limits their decision on investing in smart agriculture. Other barriers were inadequate access to agricultural credit followed by the high cost of improved crop varieties and limited government support with farm inputs.

A different approach was taken by (Jellason, et al., 2021), again for a developing country. The authors applied participatory learning methods and action (PLA) as a tool to train and teach farmers about climate-smart agriculture practices. As a final result, they found that the practice with the highest non-adaptation rate was water harvesting and small-scale irrigation, and the main barrier to that was lack of infrastructure (no water harvesting structures) and lack of finances and support.

(Yameogo, et al., 2017) found similar barriers, stating the high cost of hardware as a major barrier to implementing the latest technologies. (Mizik, 2021) also summarize the same barriers in different developing countries and areas around the globe.

In summary, one of the main problems seems to be the lack of understanding and communication between agriculture business and engineers and scientists that are developing the technology, like robots, drones, and different types of tech equipment that are supposed to help farmers in different ways, and on the other side, we have farmers that basically are "ignoring" this development and continuing with the traditional way of farming.

3. METHODOLOGY

We use questionnaires to understand the gap between technology and agriculture, thus our methodology is quantitative. The quantitative methodology is usually used to gather statistical and numerical data through questionnaires or polls and then analyze that data to conclude the results (Coghlan & Brydon-Miller, 2014) (Allen, 2017). In our paper, we gathered data through questions that were prepared through consultation with experts in the agricultural field, in order to collect accurate data for our case. Collected data is evenly distributed geographically from different regions of Kosovo in order to analyze if the behavior of farmers is different based on their region. The questions mostly focus on how big the land of the farmer is, what type of crops they plant, what opinion they have about technology in agriculture (with a focus on soil analysis), and what type of barriers they encounter when it comes to implementing technological devices in their daily routine.

After the data collection, we discuss what creates the practical gap between technology and agriculture, and what possible

technologies would be an option for these farmers based on their opinion collected from the questionnaire.

The first questions focus on things like the demographics of the farmers, the size of the land they work on, what type of plants they are growing, etc. The following questions are more specific to farming like what type of fertilizers they use, how they irrigate, if they analyze soil before planting, etc., and by that we explore indirectly if the farmer is embracing new ways of farming or still sticking with traditional methods of farming. The final questions address the thoughts of farmers directly, i.e. how much they think that technology could improve their daily work, how much would they invest in technology, what are the main barriers they think hold them to apply technology or invest in it, etc.

We conducted the survey with 50 farmers, and the demographic distribution was equal which gives us a more comprehensive view of the situation. To be more specific and not ask questions just generally about technology, we focus on soil fertilizing and analyzing the topic, which is one of the most important parts when it comes to increasing productivity, but also in terms of environmental protection (Ouyanga, et al., 2018).

4. RESULTS

One interesting result is about soil analysis.

Do you analyze the soil before planting and fertilizing?

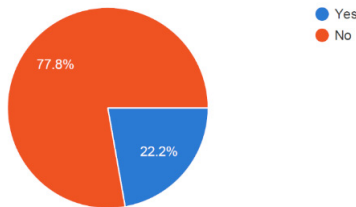


Figure 1. Soil analysis and fertilizing results from the questionnaire.

We see in figure 1 that most farmers do not do soil analysis both before planting and fertilizing. The following question about farmers opinion on the impact of the tech equipment indicates a bit about the reason for that.

On the other side, we see in figure 2 that almost half of the farmers think that technological equipment related to soil

How much do you think technological equipment (for planting, soil anal fertilization, etc) can help increase production?

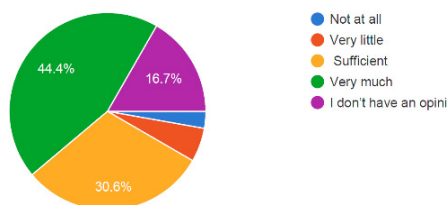


Figure 2. Opinion of the farmers about the impact of the tech equipment.

analysis and fertilization can improve the production of crops. So here we can see the first implications that farmers are actually willing to use technology but mostly are held back for different reasons. And this can be supported even more based on figure 3 where almost half of the farmers are willing to spend more than 500€ in technological investment.

How much money would you invest in technological equipment for soil analysis?

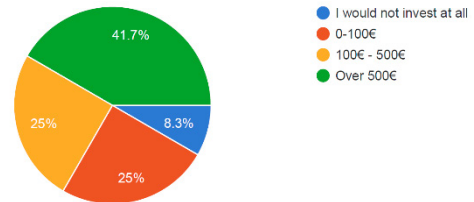


Figure 3. Opinion of the farmers about how much would they invest in technology.

These results bring us to our problem statement question which is what are the reasons that farmers are still not investing and implementing technology at a satisfactory level?

What are the barriers to investing in agricultural technological equipment?

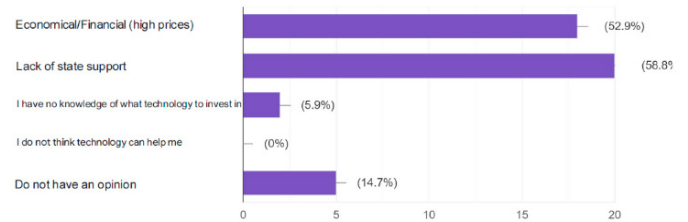


Figure 4. Identified barriers by farmers.

We can see from the results in figure 4 that mostly the barriers are of financial nature which is expectable from developing and emerging countries like Kosovo. But we also see that more than 20% of farmers neither don't have an opinion nor the knowledge on what type of technology to invest in. Based on the results from figure 3 we see indications that farmers are not investing in technology because they are not feeling safe and not because they don't have the resources or the will to do it. And that can be related also to the results about how much are they satisfied with their harvest in the past. We can see in figure 5 that almost half of the farmers are usually satisfied or very satisfied which indicates that they have the resources to invest in technology, it is only a matter of persuasion.

Are you satisfied with the harvest from the past?

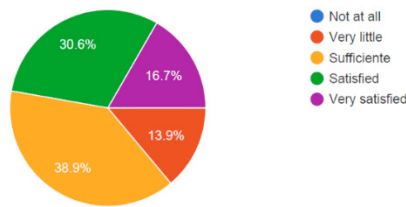


Figure 5. Satisfaction level of farmers with their harvest.

5. DISCUSSION

We see from the results that a high percentage of farmers mostly do not have an opinion about how much technology can help them, and also, that they are mostly willing to invest a small amount of money in technology. Additionally, financial barriers lead as the main reason that hold farmers from investing in technology, but also, we have a considerable number of them that do not have an idea what type of technology they could use for farming. On the other side, we see that in some developed countries farmers have doubts about the state of the art technology and clearly show a disconnection between what is being developed by engineers/scientists and what is the need of farmers (Long, et al., 2016). That mostly includes robots and drones being used in agriculture, with most of the cases accompanied by IoT and AI (Friha, et al., 2021) (Mandal, et al., 2022) which is often complex, high-cost, and not accessible to farmers. Besides that, in most cases, these technologies either are in the testing phase or implemented on a small scale for experimenting and not adopted on a large scale.

We suggest that a good option, in that case, would be to approach farmers with smart but simple solutions that include technologies such as AI, but with low complexity for users, low cost, and measurable results at the end. One good example is a soil analysis device that tells the farmer exactly about the state of the soil and what intervention, e.g. fertilizer or amount of water, is needed depending on the type of crop that is going to be planted. However, in order to make it more practical, the device needs to be simple like an everyday tool of a farmer, and not some complicated device that needs a lot of knowledge and effort to be used.

Also, features like IoT will probably complicate it, since in the rural areas and emerging countries' access to the internet is limited.

Consequently, in order to build such a device (or a similar one), we need to process information like images or sensor data in the device and not depend on cloud computing or expensive mobile computers, since the device will operate in the field and give real-time information to the farmer. One of the best options for such a solution would be edge computing since we know that with it, we can compute and process all the information directly in the embedded device without the need for an internet connection or sending data to other processing centers (Mansouri & Babar, 2021). And with the latest developments, we now have AI implemented into edge computing (edge intelligence) (Zhou, et al., 2019) which can

make it possible to process complex tasks with small embedded devices without the need for extra computing power or cloud computing. There is already a lot of cheap embedded hardware in the market like ESP boards, Raspberry Pi, and even some Arduino boards that support the development of AI algorithms like neural networks or image processing within a board (Chen & Ran, 2019). With such options, there is a possibility to build a smart and cheap embedded device that is practical and will help a farmer with his daily tasks, and as such will have more impact more quickly than other expensive developments that are mostly in the research phase.

6. CONCLUSIONS

As previous research from other authors and our own research indicates, farmers in both developed and developing countries are still preferring traditional methods over using the latest technology like drones or robots in their daily work. And even though reasons for that may be changing between developing and developed countries, in the end, most of the farmers in one way or another don't trust emerging technologies in order to spend their money on that. One of the reasons for that is the lack of proper communication and understanding between farmers and engineers where the last ones usually develop technologies that either end up with a high price or are very complicated and time-consuming to understand for farmers. Also, we see that most of the high-tech solutions are still in the prototype phase of system tests for different use cases e.g. different types of soil, different weather, different plant, etc. Based on that, we suggest cheaper solutions that still solve complex tasks and help farmers without being too complicated to use or having features that are not that practical for farmers.

We recommend simplification of the complex devices and achieving that using low-cost embedded systems. Such systems are being developed by various producers and the development is advancing fast. The increasing popularity of AI implementation in such devices (Zhou, et al., 2019) is also an indicator for such devices to become an ideal all in one solution. Even though the bottom-up engineering approach helps in solving complex engineering challenges, in cases like this one, the top-down approach focusing on the farmers' needs seems to be crucial in order to find fitting solutions for the daily problems of the farmer.

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