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Factors Influencing Precision Agriculture Tools or Technologies Adoption in Egypt

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Abstract

Precision Agriculture Technologies (PATs) are advocated as inevitable agricultural practices to achieve the highest economic value and mitigate the environmental impact of the agriculture.

Water scarcity and rapid population growth in Egypt endanger the economic nourishment. Since agriculture consume more than 80% of total water consumption in Egypt; it is important to adopt efficient practices without sacrificing high productivity and minimize environmental degradation. This thesis studies the factors influencing PATs adoption in Egypt. Based on the literature review; there are 5 constructs with 15 independent variables are tested in this study. The constructs are as follows; (1) Socio Demographic Factors; studying effect of farmer age, level of education, years of experience. (2) Agro Ecological Factors; including farm size, land tenure, farm crops. (3) Financial Factors; encompasses farm income, investment cost, perceived economic benefits and perceived environmental benefits. (4) Technological Factors; testing impact computer and smart phone usage, PATs and PI Usage and perceived ease of use. (5) Institutional Factors: investigating effect of farm region and development pressure.

Non-probability sampling was used in this study with convenience and snowball techniques to collect data. The data was collected from 32 farms distributed in Lower and Upper Egypt via an online survey published through Social Media Channels. Respondents were the farm owners and farm operators as each one represents one farm only. The analysis was performed using SPSS to discover factors impacting PATs adoption. Results show that perceived environmental benefits and development pressure are statistically significant factors affecting PATs adoption in Egypt.

To conclude, this study provides insightful results regarding what influences the Egyptian farmers in PATs adoption and this may provide better understanding for policy makers to better formulate incentive programs and regulation to motivate farmers to adopt more PATs. Moreover, these results can be used by service providers to enhance marketing.

Keywords: Precision Agriculture, Technology, Adoption, Factors, Sustainability.

1. Introduction

Basically, Precision Agriculture or the so called "Precision Farming" is relatively new methodology in agriculture and farm management that was firstly introduced in the 80s (Pierpaolia, Carlia, Pignattia, & Canavaria, 2013). It is based on the notion of a holistic integration farm management that strives to eliminate environmental impact and reduce cost by putting into consideration different variables and perform all the required practices with guaranteed ideal application (Pierpaolia, Carlia, Pignattia, & Canavaria, 2013; Uddin, 2020). Moreover, Precision Agriculture Technology has proved higher yields than the conventional agricultural practices (Uddin, 2020). Over time, a lot of Precision Agriculture Technologies (PATs) were introduced starting by Geographic Information System (GIS) used to monitor the yields in the 90s till the most recent updated technologies in Variable Rate Application (VRI) in the fertilizers and water application and auto-steer machines (Uddin, 2020). This study will investigate the factors influencing adoption of some of the Precision Agriculture Tools/Technologies, particularly, tools that are concerned directly with saving water.

The research used the Nine elements model/framework by Elsafty (2018, 2019, 2020, 2021) to analyze the context as the model has nine main elements, yet, the researchers focused on only four elements out of nine for applicability to this research's phenomena, and has been used in several research papers (Elsafty, A., Elsayed, H., & Shaaban, 2020; Elsafty, A., & Abadir & Sharawy, 2020; Elsafty, A., Elbouseery, I., & Shaarawy, A., 2020; Elsafty, A., & Elzeftawy, A., 2021/2022; Elsafty, A., & Elshahed, M., 2021; Elsafty, A., & Osman, M., 2021; Elsafty, A., & Lydia, S., 2022; Elsafty, A., & Shaarawy, M., 2022).

Food and Agriculture Challenges

- Population Growth

Food and agriculture sector is facing one of the biggest challenges of boosted demand as a result of exponential population growth (Trendov, Varas, & Zeng, 2019). By 2050 world population is estimated to reach 9.6 billion (UN DESA, 2019) which will create a huge demand for food and agricultural products.

In the same time, developing countries must adapt more sustainable agricultural practices to be able to face the climate change problems that affect productivity and natural resources (FAO, 2009). Moreover, the income growth for low- and middle-income countries will fasten the change in the dietary behaviors, as people will switch from cereals to meat, fruits and vegetables which will definitely put huge pressure on the natural resources (FAO, 2017).

- Productivity Challenges Globally

As population is expected to be over 10 billion after 2050 (UN DESA, 2019) and either this population is from urban or rural areas, they will need food and fiber to satisfy their physiological needs to survive. Consequently, it is necessary that agriculture productivity has to increase globally by 70% by 2050. Further, because agriculture consumes 70% of the fresh water withdrawals worldwide, in water stressed regions it is recommended to reassign 25% to 40% of water to shift from lower agriculture productivity to higher levels (The World Bank, 2020).

- Water Scarcity Globally

Water scarcity is a serious problem that hits many countries around the world. Water consumption has been doubled in this century compared to the previous century (UN DESA, 2014). In addition, climate change, pollution and increasing demand for water will contribute to more water scarcity issues and will create a sense of urgency to execute more sustainable development plans to avoid having 1.8 billion people by 2025 with a serious water scarcity crisis (UN DESA, 2014).

Additionally, climate change is one of the critical escalating challenges that threaten water and affect badly the integrated relationship between economic development and water needs all over the world, that's why, water should be treated sensitively as a scarce resource (United Nations - UN Water, No Available Date).

- Water Scarcity in Egypt

According to the Central Agency for Public Mobilization and Statistics (CAPMAS); agriculture sector has the biggest portion of water consumption in Egypt by 81% of total use, comes after it the drinking water with 13.6% in year 2016 (CAPMAS, 2017).

Egypt suffers from water poverty because according to the World Health Organization (WHO), a person needs 50-100 liters per day to fulfill his/her essential physical needs (UNDP, No Available Date). In Egypt, according to CAPMAS, the per capita share of water has dropped by 60% in 66 years and estimated to reach a dangerous level of water scarcity by 2025 (UN DESA, 2014; Ahram Online, 2014). In a report by CAPMAS, articulated that Egypt in year 1947 had a surplus of water per capita of 2,526 cubic meters annually, afterwards in 1970, it reached 1,972 cubic meters and then declined in 2013 to reach 663 (Ahram Online, 2014) which is near to absolute water poverty level (UN DESA, 2014).

Nevertheless, the national challenges are not only the main problem because Ethiopia has built a huge dam that is considered the most enormous hydroelectric dam in Africa and Egypt has declared that this dam will affect their Nile water share (Ahram Online, 2014). Consequently, water resources have to be treated very sensitively considering accurate management of usage with high efficiency goals (United Nations - UN Water, No Available Date).

Digital Transformation in Agriculture

Innovative digitization is essential to agricultural entities in order to increase and stabilize farms' productivity rates. By adopting the new trends in digital technologies, companies or farmers can leverage dealing with the accelerating challenges of climate and water scarcity dangers with minimum environmental effect (Trivelli, Apicella, Chiarello , & Rana, 2019) and at a lesser cost (Accenture, 2017).

Global Major Drivers for Agriculture Digital Transformation

The following figure shows ten drivers that elicit the adoption of digital transformation in agriculture:

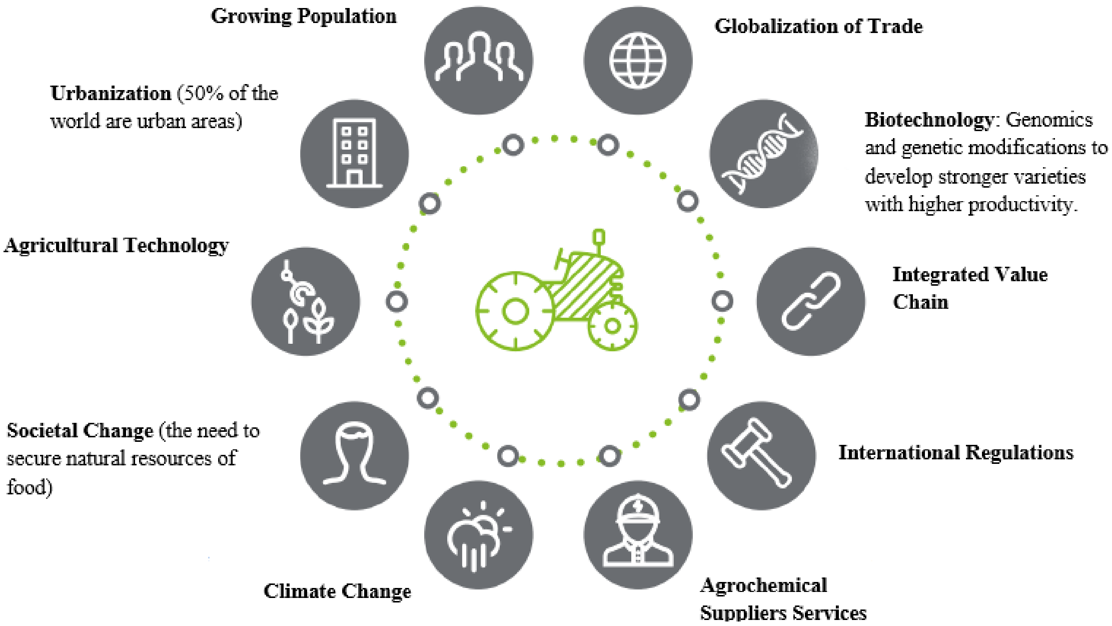

Figure 1. Global Major Drivers for Agriculture Digital Transformation

Source: (Laugerette & Stöckel, 2016)

There is high potential in adopting digital technological tools to help farmers make effective decisions regarding farming activities especially, to achieve higher profitability using Data-driven insights. In addition, this will make the agriculture field more appealing to the young generation (European Commission, No Available Date).

By emerging big data analysis with other digital tools, huge digital data that are coming from different inputs due to better engagement with cloud systems with different formatting, these data can be analyzed and help all the stakeholders of the value chain to make effective strategic decisions.

Problem Definition

One of the most serious dangers posed by fast population expansion is the rising need for food on a national and global scale and thus, putting enormous pressure on plants and grains production needs (Trendov, Varas, & Zeng, 2019; UN DESA, 2019). That's why, for three years in a raw, the ratio of people who suffer from hunger worldwide is increasing (FAO, 2018).

Furthermore, despite Egypt's increased agricultural outputs throughout the past decades, farmland production has never achieved its ultimate potential (MALR, 2009). Additionally, Egypt has been afflicted by poor agricultural and irrigation practices which have harmed a variety of crops and as a result it reflected on the national export deficiencies (El-kader & El-Basioni, 2013).

Although Egypt suffers from a serious water scarcity problem, a lot of agricultural spaces in Egypt are wasting a lot of water and fertilizers due to traditional irrigation systems that are also affecting badly the farm productivity, given that agriculture irrigation takes 80% of the whole country water consumption (The World Bank, 2018; CAPMAS, 2017).

According to a lot of researches in Precision Agriculture; using these tools and technologies increase productivity and ensure minimizing the environmental impact (Ess & Morgan, 2003; Say, Keskin, Sehri, & Sekerli, 2018; Rains, & Thomas, 2009).

Problem Validation & Research Gap

According to MALR (2009); Egypt's vision of 2030 in agriculture encompasses pushing the national polices to induce farmers to adopt more efficient equipment and precise practices for the sake of saving natural resources, so as, increase the croplands' yield levels.

As for the above-mentioned statistics regarding water deficiency and agricultural productivity problems nationally and globally; the researcher found that it makes a lot of sense studying factors affecting Precision Agriculture Tools/Technologies' adoption in order to introduce a comprehensive overview on influential factors of adopting

Precision Agriculture technologies by the Egyptian farmers.

Moreover, after reviewing the provided literature studying factors that influence PATs' adoption, the researcher has discovered that no research has been conducted on Egypt' case to explore the factors that impact PATs' adoption.

2. Systematic Literature Review on PATs Adoption Trends in Developed and Developing Countries

- Adoption Trend in Developed Countries

USA is one of the most prominent countries worldwide adopting PATs as US is a world leader of producing and adopting innovative technologies (Say, Keskin, Sehri, & Sekerli, 2018). Fountas et al., (2005) stated that around 90% of yield monitoring tools worldwide were adopted by US farmers. Regarding auto guidance system; around 60-80% utilized this system (Erickson & Widmar, 2015) (Miller, Griffin, Bergtold, Sharda, & Ciampitti, 2017). Yield monitors and VRT were more famous earlier, meanwhile, recently auto guidance systems got prevalent (Norwood & Fulton, 2009; Schimmelpfennig & Ebel, 2011). Very soon, auto guidance system will be a conventional technology in the developed countries as nowadays, driverless machinery is being tested and soon, will be introduced to the PA market (Say, Keskin, Sehri, & Sekerli, 2018).

Table 1. Adoption Trend in USA:

Country/State	Technology/Adoption Rate	Citation
USA	By 2003, around 90% of yield monitor technology in the world were utilized in USA	(Fountas, Pedersen, & Blackmore, 2005)
USA/Ohio	36% of the sample in the study had at least one tool from Precision Agriculture	(Isgin, Bilgic, Forster,, & Batte, 2008)
USA	In 2005, 25% of Corn croplands used yield monitors, so as, 10% of winter wheat crop in 2004 and 22% of Soybeans	(Griffin & Erickson, 2009)
USA	54% of the selected sample used minimum one tool of PA. 32% of them used yield monitor and 32% auto-steer technologies	(Norwood & Fulton, 2009)
USA	PA adoption rate of 85% from agricultural dealers	(Whipker & Akridge, 2009)
USA/12 States	About 34% of cotton farmers used PA tools	(Paudel, Pandit, Segarra, & Mishra, 2011)
USA/ Corn Belt Region	40% of grain acres used Yield Monitoring, 24% adopted Prescription maps using GPS and 16% used VRT. In Soybean croplands, 17% used GPS maps and 12% used VRT	(Schimmelpfennig & Ebel, 2011)
USA /34 States	A survey for dealerships resulted for 65% adoption rate for GPS control system with manual options and 61% auto-steer machinery	(Holland, Erickson, & Widmar, 2013)
USA	The most widespread PATs were GPS guidance auto-control and manual control with 64%, auto-steer with 83% and GPS enabled sprayer with 74%	(Erickson & Widmar, 2015)

Table 2. PATs Adoption Rate in Other Developed Countries

Country	Technology/Adoption Rate	Citation
Australia	VRT adoption rate increased by 20% nationally between 2008-2009	(Robertson, et al., 2012)
Canada	According to a survey conducted in 2005, 77.9% utilized guidance system, 23.3% used equipment with GPS facility, 23.5% used VRT in fertilizers application and 27% in pesticides application	(Haak, 2011)
Canada/Western	98% utilized GPS guidance system, 84% had minimum one PAT and 75% showed willingness to use PATs more in their operations	(Steele, 2017)
Europe	70% of all fertilizers and pesticides machines contained PA technologies. However, 25% of all the farms in EU use PA tools	(Armagan, 2016) **-** (EPRS, 2016)
Europe/ Denmark/ Britain/ Germany	In year 2000, around 400 farmers in Denmark, 400 farmers in Britain, 300 farmers in Sweden and 200 in Germany used Yield Monitor technology	(Fountas, Pedersen, & Blackmore, 2005)
Europe/ England	A dramatic increase in adoption occurred comparing year 2009 to year 2012; GPS usage increased from 14% to 22%, Soil Mapping adoption rate increased from 14% to 20%. VRT usage increased from 13% to 16% and Yield Mapping increased from 7% to 11%	(DEFRA, 2013)
Europe/ France	150,000 hectares are operated through using PA technology	(Invivo, 2016)
Europe/ Germany	A result from a survey showed that between 6.6% and 11% of farmers are using GPS based tools for Soil Sampling	(Reichardt, Jurgens, Kloble, Huter, & Moser, 2009)
Europe/Germany/ Finland/ Denmark	36% of the surveyed audience had a prior experience using PA technologies	(Bligaard, 2013)
Europe/ Sweden	20% used Nitrogen sensors in wheat croplands	(Söderström, 2013)
Europe/ UK	60% of the farmers in UK has PA tools and this implies sometimes just using auto-steering tractors	(Norris, 2015)
Japan	In 2014 22% of rice croplands were using auto-steering machinery in pesticides application	(Liao, 2017)

Table 3. PA Adoption Trends in Developing Countries

Country	Technology/Adoption Rate	Citation
Argentina	It is ranked the second country after US in using Yield Monitoring and fifth country in Yield Monitors distribution of 51 monitors per 1 million hectares. 4% of the farms were harvested using Yield Mapping technology and around 560 Yield Monitor were acquired in 2000	(Mondal & Basu, 2009) (Bongiovanni & Lowenberg-DeBoer, 2005)
Brazil/ Sao Paolo State	58% of domestic and 38 of sugar and ethanol companies utilized PATs. Most common technologies were satellite imaging by 76%, soil sampling with GPS by 31%, autopilot by 39% and VRT by 29%	(Silva, Moraes, & Molin, 2011)
Brazil	89% adopted GPS guidance with manual options while 56% chose to get it with automated control and yield mapping system with 56%	(Borghi, Avanzi, Bortolon, Luchiari Junior, & Bortolon, 2016)
China/ Heilongjiang	Around 25% of the farms were using PATs in managing the agricultural activities. Most common tool is auto-steer tractors	(Verma, 2015)
India	Leaf Color Chart (LCC) one of PA mapping tool and soil sampling with laser-based system are main technologies in rice farms	(Mondal & Basu, 2009)
South Africa	In 2000, only 15 famers used yield monitoring, afterwards, in 2005 a study revealed an increase in usage that reached 600 and VRT was adopted by 244 farmers, GPS manual guidance system was used by 200 and auto GPS guidance by 60 farmers	(Helm, 2005) (Mondal & Basu, 2009)
Turkey	In 2016 about 3% countrywide had yield monitors equipped with combine harvesters. In 2017 it increased to 6% countrywide adopting yield monitoring over combine harvesters	(Keskin & Sekerli, 2016) (Erzurumlu, 2017)

Previous Models Applied on PATs Adoption Researches

According to Pierpaoli et al., (2013), articles discussing PATs adoption can be divided into two main groups; firstly, ex-post models that use utility research model. Secondly, ex-ante model which studies the adoption using predictive model type concerning user's behavior (Pierpaolia, Carlia, Pignattia, & Canavaria, 2013) (figures 2 & 3). Technology adoption is a dynamic endeavor in which a lot of factors stimulate the adoption decision (Agarwal & Prasad, 1999; Dimara & Skuras, 2003).

PA technologies that emerged by mid of 1980's is a relatively recent concept, in which, term "technology" is being associated with it at most (Zhang & Wang, 2002). In spite of conducting a lot of researches studying the environmental, economic and agronomic impact from using PATs (Batte & Arnholt, 2003; Pierce & Elliott, 2008; Swinton & Lowenberg-DeBoer, 1998), yet, adoption rate reported in academic and professional studies and surveys is relatively low in pace (Ellis, Baugher, & Lewis, 2010; Fountas, Pedersen, & Blackmore, 2005; Lamb, Frazier, & Adams, 2008). As mentioned, ex-post studies and ex-ante studies investigate factors influencing adoption decision or prior to its implementation, still, comprehensive mixed models of ex-post and ex-ante are not yet developed (Pierpaolia, Carlia, Pignattia, & Canavaria, 2013) (Tey & Brindal, 2012).

The following factors are mentioned in most of reviewed literature: (Pierpaolia, Carlia, Pignattia, & Canavaria, 2013)

- Farm size
- Land tenure
- Farm income/saving costs
- Farmer's level of education
- Location

- Use of computers
- Access to information (by application or service provider)

Most probably, the adopter owns a big farm, well educated, has a good perception of the system's benefits, has a previous experience with PATs and uses computers confidently (this is considered the second significant feature after farm size) and applying a lot of technologies and agricultural tools and practices to be able to cope with the growing competitiveness in the global markets (Pierpaolia, Carlia, Pignattia, & Canavaria, 2013; Tey & Brindal, 2012).

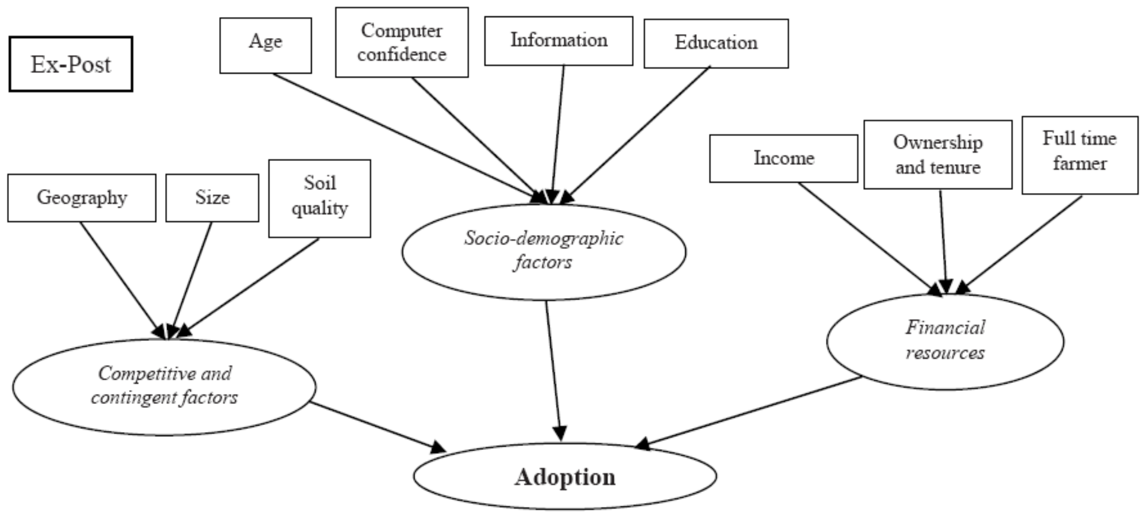

Figure 2. Ex-Post Model of PAT Adoption

Source: (Pierpaolia, Carlia, Pignattia, & Canavaria, 2013)

Ex-ante model is a Technology Acceptance Model (TAM) studying the behavior of the adopter before making the decision to adopt a new technology and clarifying the adoption phases (Davis & Venkatesh, 2004; Davis, 1989; Gefen & Straub, 2000). It is a model studies the behavior that is derived from the Theory of Planned Behavior (Ajzen, 1991; Fishbein & Ajzen, 1975) that tried to study the potential adopter intention on when and how he/she will decide acquiring this new technology (Pierpaolia, Carlia, Pignattia, & Canavaria, 2013). Accordingly, TAM model studies the perception and attitude of the potential adopters of new technologies (Pierpaolia, Carlia, Pignattia, & Canavaria, 2013). Figure 3 summarizes the factors affecting attitude to adopt PA.

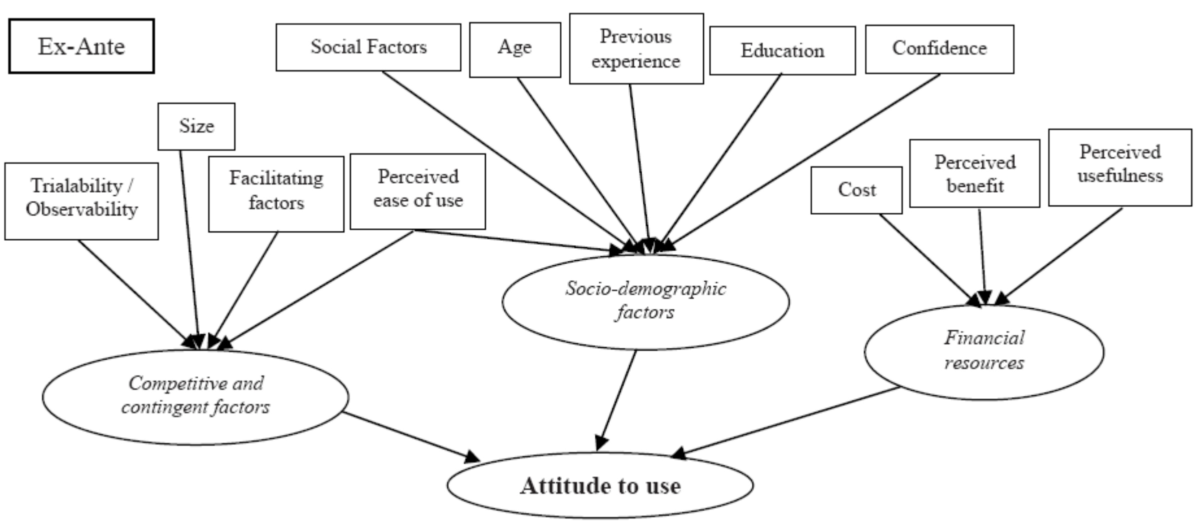

Figure 3. Factors Affecting Attitude to Adopt

Source: (Pierpaolia, Carlia, Pignattia, & Canavaria, 2013)

Categories	Variables	
Socio-economic factors	Operator age	Formal education
	Years of farming experience	
Agro-ecological factors	Land tenure	Part-owner farmers
	Farm specialization	Full-owner farmers
	Farm size	Farm income/profitability
	Farm sales	Soil quality
	Variable fertilizer rates	Percentage of main crop in total farmland
	Livestock sales	Percentage of farmland as county land area
	Debt-to-asset ratio	Percentage of cropped land to total farmland
	Production value	Percentage of farmland as large farms
	Owned land minus rented land	Off-farm employment
	Yield	
Institutional factors	Distance from a fertilizer dealer	Use of forward contract
	Region	Development pressure
Informational factors	Use consultant	Perceived usefulness of extension services in implementing precision farming practices
Farmer perception	Perceived profitability of using precision agriculture	
Behavioral factors	Willingness to adopt variable-rate technology	
Technological factors	Yield mapping	Farm has irrigation facility
	Use of computer	Generated own map-based input prescription

Figure 4.Tey & Brindal (2012) Selected Variables

Source (Tey & Brindal, 2012)

Some literatures showed neglection of TAM while studying the adoption of PATs, such as Tey & Brindal (2012) who neglected perception and behavior, purchase intention, as well (Pierpaolia, Carlia, Pignattia, & Canavaria, 2013). However; after reviewing Tey and Brindal (2012)' model, from the researcher's point of view; they did not neglect the perception of the adopter neither the behavioral factors as they included in their conceptual framework some independent variables that investigated the perceived profitability, perceived ease of use (using a consultant or service provider or not) and behavioral factors were introduced in terms of technological factors e.g., either the potential adopters deals with computers and whether the farmer has irrigation technological tools or not (Tey & Brindal, 2012) (Figure 4).

3. Methodology

Based on Tey and Brindal review on 25 papers they chose a set of constructs with group of independent variables and were used by Kolady et al., (2020) but with more simplified and summarized independent variables. Hence, the researcher used same variables used by Kolady et al., (2020) and added some important variables from Tey and Brindal (2012) according to the opinion of an expert.

Figure 5 represents the selected set of independent variables and their relation with PATs adoption decision. These variables and hypothesis associated with each of them included in the design. Although these variables are supposed to affect the adoption decision as mentioned in most of the countries such as USA, Australia Canada and other countries, it is still uncertain to find the same significant factors in Egypt case as this will be investigated in this study.

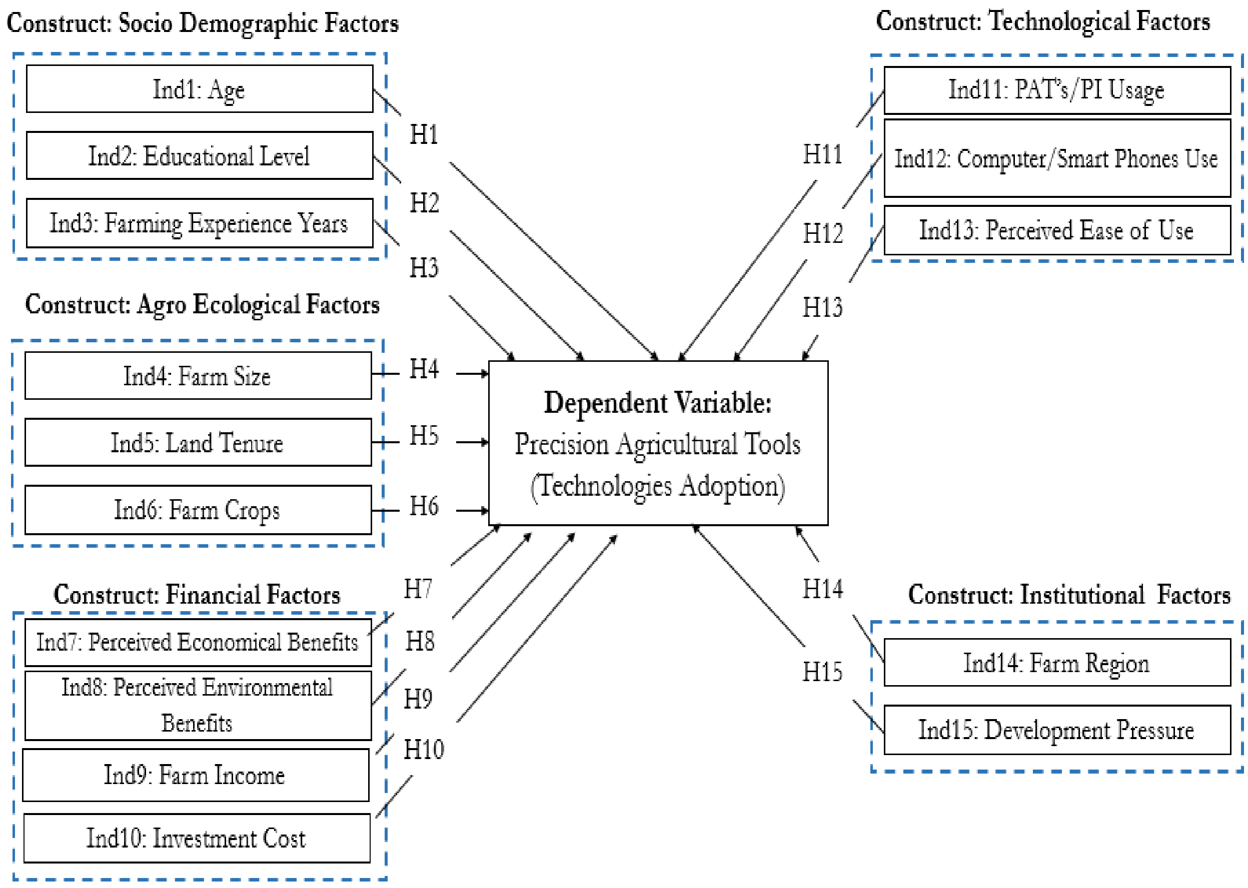

Figure 5. Theoretical Framework

Source: Researcher's Elaboration on research model studies of Tey & Brindal (2012), Pierpaolia et al., (2013) and Kolady et al., (2020)

Precision Agriculture Tools/Technologies Adoption is the dependent variable in this study.

Socio Demographic Factors

The personal characteristics of the farmer is proved to have a significant effect on the adoption decision of the PATs (Pierpaolia, Carlia, Pignattia, & Canavaria, 2013; Tey & Brindal, 2012).

Agro-Ecological Factors

According Tey and Brindal (2012) in their review of a massive number of studies, they have summarized these factors to include the following factors that represent the physiological farm characteristics, such as; size, ownership status, cultivated crop types and soil fertility, however; soil fertility will be included in another construct to unify the meaning and measurements.

Financial Factors

This construct is one of the most important aspects in variables affecting PATs adoption as farmers focus at the utmost financial benefit from every new investment or technology they acquire.

Technological Factors

Technology usage indicates a strong probability of having a sort of readiness to adopt the PATs and is perceived as a crucial factor that manipulates adoption decision (Larson, et al., 2008; Tey & Brindal, 2012).

Institutional Factors

It compiles the factors affecting farmer's desire to adopt emerging technologies of Precision Agriculture or cause discouragement to the farmer to improve his/her operations (Tey & Brindal, 2012)

Considering, that the researcher has highlighted two crucial problems that tremendously threatens Egypt which are; water scarcity and agricultural productivity problems that hold back reaching the utmost export potentials.

Therefore, based on an interview with an expert in the agriculture field, the PATs that are directly connected to water and fertilizers application are as follows;

1) Prescription Field Mapping
2) Variable Rate Technologies
3) Sensing Systems
4) Soil Grid Sampling
5) Precision Irrigation Tools/Technologies

The researcher used non-probability sampling method with convenience and snowballing sampling technique. The researcher used the personal network and membership in formal and informal groups and association. Bearing in mind, that this sampling method does not represent the general population, thus; results cannot be generalized (Sekaran & Bougie, 2016).

4. Data Analysis Methods

The researcher collected data using an online survey. The data was analyzed using SPSS program for the following statistical analysis;

- Cronbach's Alfa analysis to test reliability and consistency of the questionnaire items.
- Descriptive analysis for all the questionnaire items.
- Correlation analysis to test the strength of the relationship between the independent variables and the dependent variable. In this regard, the researcher used three different Correlation tests according to the tested variables' type;
  - Pearson Correlation
  - Kendall's Coefficient of Rank
  - Biserial Correlation
- Regression Analysis: Simple and Multiple Linear Regression analysis to test the significant predictor's impact on the dependent variable

The researcher succeeded to collect data from 32 respondents. In fact, all the respondents are either farm owners or agricultural engineers who work in farms as technical managers.

On the other hand, due to cultural issues with farmers in Egypt, usually farmers specifically, do not feel comfortable providing any data regarding their business and prefer secrecy. That's why in the beginning the researcher had to open the scope of the sample to include non-exporter farms.

Summary of Descriptive Analysis

The survey included items to describe demographics of the respondents and items to test the 15 independent variables mentioned in the theoretical framework.

Age

Age mean= 38 while median=33 and mode=30 which means that most of the respondents are around mid of 30s

Gender

According to the demographic analysis of the study; 96.9% were males while only 3.1% represents female participance in the survey. This is considered reasonable because as per Kandeel (2017) culture in Egypt in land heritage; usually women get neglected because men who take these kinds of properties and be responsible for the farm management. Bearing in mind, the sample is not representative of the population.

Level of Education

The sample is considered to be highly educated as 65.6% hold University degree, 15.6% have Master degree and 15.6% have Doctoral degree.

Farming Experience

As per the mean value of this variable; the researcher concluded that most of the respondents have a considerable farming experience. Moreover, the most repeated answer was 5 years of experience.

Farm Size

According to the descriptive analysis, 40% of the respondents have farms or work at farms that are more than 300 feddans, 18% are from 10-50 feddans and the rest are scattered between rest of farm size categories. Therefore, majority of participants own or work at big farms by 40%.

Land Tenure

Analysis showed that 65.6% of respondents own the farms and 34.4% rent the lands that are under their operation.

Farm Location

As per the descriptive analysis; 90.6% have or work at farms that are located in Lower Egypt while the rest are located in upper Egypt.

As referred before, Lower Egypt has more advanced infrastructure than Upper Egypt in food and agriculture sector. However; Upper Egypt has more fertile soil and usually get higher productivity levels than farms in Lower Egypt.

Farm Crops

Majority of the respondents who answered that they plant fruits resembled 46.9% of the data sample, comes after them participants who plant Vegetables by 34.4% and the rest are scattered between Hydroponics, Aquaponics, Green House, Sugar Beet and Medicinal plants.

Farm Income

As for the profit per feddan; 56.3% chose not to respond to this question. That supports the concept that is mentioned previously as farmers in Egypt prefer not to share information regarding their business performance especially when it comes to profit.

The rest of the respondents were distributed as follows; 15.6% made profit more than 50k per feddan, 12.5% made profit per fed. of 5k-10k, while 9.5% made less than 5k and 6.3 made 10k-20k.

Exporter or Non-Exporter Farms

Farms that export resembled 65.6% of the sample size, meanwhile 34.4% do not export. However; the researcher concluded that it is not necessarily for a farm to export to use PATs in their operation because as per description of the sample, all non-exporter farms use at least one of the PATs.

PATs & PI Usage

The scope of this study is limited to the PATs that are directly connected to water and nutrients application. They are as follows;

- Prescription Field Mapping (71.9%)
- Variable Rate Application (81.3 %)
- Soil Analysis (84.4%)
- Sensing System (50.0%)

The biggest intersection is between variable rate application and soil sampling with percentage 75%. While the lowest percentage of intersection is between Sensing System and Field Mapping by 43.8%.

PI Tools/Technologies

- Automated system 46%
- flow meter 66.7%
- VRI 90%
- Data collection & Analysis 60%

The biggest intersection is between VRI and Irrigation Flow Meter by 60%, while, the lowest percentage of intersection is between Data collection and Analysis and Automated system

Over and above, 50% of the respondents use these technologies by themselves without help of a consultant. However; 40% of the respondents let the consultant use them which means they do not have the qualified caliber to implement such advanced technologies. Besides, only 3.1% of the respondents use custom application to perform all these practices with minimal human interfere.

Over and above, figure 6 shows that 34.3% of the respondents use Automated Irrigation Systems with flow meter and use Data collection tools. Further, 43.7% of the participants use Sensors, apply Variable Rate Application in their irrigation and fertilizing and as a baseline for these practices; it is normal to find them apply Prescription Field Mapping.

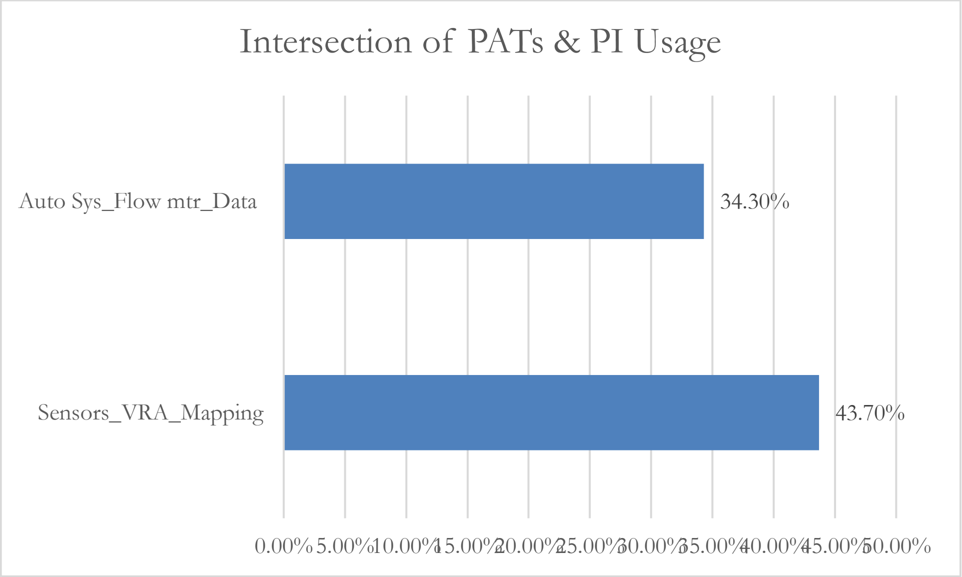

Figure 6. Intersections Between PATs Usage

Computer and smart phones usage

- Accounting (87.1%)
- Record Keeping (83.9%))
- Farm Supplies and purchases (77.4%))
- Marketing information (64.5%))

Phone usage

- Weather monitoring (71%)
- Market information (87.1%))
- Soil Sampling (25.8%))
- Field Scouting (25.8%))

Figure 7 shows the high usage of multiple activities using computer than smart phones' advanced application.

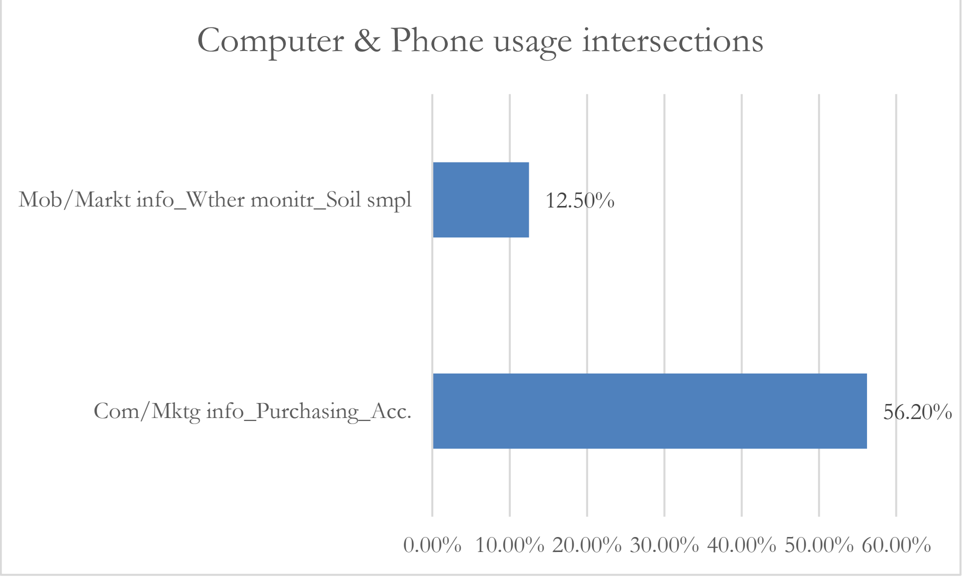

Figure 7. Usage Intersections of Computer and Smart Phones

Development Pressure

Descriptive analysis showed that 78.13% know a friend or a neighbor who adopted at least one of the previously-mentioned PATs, while, 21.8% answered that around their network, no one adopted PATs.

Dependent Variable "PATs Adoption"

As per mean and median values for PATs adoption; mean=4.625 and median= 5, that means that most of the respondents tend to strongly agree and agree on adopting PATs.

As for descriptive analysis for the scale items;

- **Perceived Economic Benefits:** Respondents tended to strongly agree on the importance of the Economic Benefits by adopting PATs.
- **Perceived Environmental Benefits:** Respondents tended to strongly agree on the important role of the Environmental Benefits by adopting PATs.
- **Investment Cost:** Respondents tended to answer neutral (not agree nor disagree) to investment cost risk of PATs.
- **Perceived Ease of Use:** Respondents tended to be neutral (not agree nor disagree) about Ease of Using PATs.

Correlation Analysis:

1) Pearson Correlation Analysis

Table 4. Pearson Correlation

Independent Variables	Dependent Variable (PATs Adoption)		Relationship Strength	Statistical Significance
Age	Pearson's Coefficient	-.089	No relation or very weak	Statistically Insignificant
	Sig. (2-tailed)	.629		
Farming Experience Years	Pearson's Coefficient	.006	No relation or very weak	Statistically Insignificant
	Sig. (2-tailed)	.972		
Perceived Economical Benefits	Pearson's Coefficient	.274	Weak	Statistically Insignificant
	Sig (2-tailed)	.129		
Perceived Environmental Benefits	Pearson's Coefficient	.469**	Moderate	Statistically Significant
	Sig (2-tailed)	.007		
Investment Cost	Pearson's Coefficient	.120	Weak	Statistically Insignificant
	Sig (2-tailed)	.513		
PAT's / PI usage	Pearson's Coefficient	.232	Weak	Statistically Insignificant
	Sig (2-tailed)	.202		
Computer /Smart Phones usage	Pearson's Coefficient	.330	Moderate	Statistically Significant
	Sig (2-tailed)	.065		
Perceived Ease of use	Pearson's Coefficient	.196	Weak	Statistically Insignificant
	Sig (2-tailed)	.283		

2) Kendall's Coefficient of Rank Correlation (Kendall tau-sub-b, τb)

Table 5. Kendall's Coefficient of Rank Correlation

Independent Variables	Dependent Variable (PATs Adoption)		Relationship Strength	Statistical Significance
Educational Level	Correlation Coefficient	-.112	Very weak	Statistically Insignificant
	Sig (2-tailed)	.499		
Farm Size	Correlation Coefficient	-.034	No relation	Statistically Insignificant
	Sig (2-tailed)	.828		
Farm Income	Correlation Coefficient	.108	Very weak	Statistically Insignificant
	Sig (2-tailed)	.501		

Point Biserial Correlation Coefficient

Table 6. Point Biserial Correlation

Independent Variables	Dependent Variable (PATs Adoption)		Relationship Strength	Statistical Significance
Land Tenure	Correlation Coefficient	.010	No relation	Statistically Insignificant
	Sig (2-tailed)	.958		
Farm Region	Correlation Coefficient	-.141	Very weak	Statistically Insignificant
	Sig (2-tailed)	.442		
Development Pressure	Correlation Coefficient	-.408*	Moderate	Statistically Significant
	Sig (2-tailed)	.020		

Table 7. Point Biserial Correlation Continued

Independent Variables	Dependent Variable (PATs Adoption)		Relationship Strength	Statistical Significance
Vegetables	Correlation Coefficient	.298	Weak	Statistically Insignificant
	Sig (2-tailed)	.098		
Fruits	Correlation Coefficient	-.338	Weak	Statistically Insignificant
	Sig (2-tailed)	.059		
Green House	Correlation Coefficient	.188	Very weak	Statistically Insignificant
	Sig (2-tailed)	.302		
Aquaponics	Correlation Coefficient	.131	Very weak	Statistically Insignificant
	Sig (2-tailed)	.475		
Medicinal – Aromatic Plants	Correlation Coefficient	-.079	No relation	Statistically Insignificant
	Sig (2-tailed)	.669		
Sugar Beats	Correlation Coefficient	-.288	Weak	Statistically Insignificant
	Sig (2-tailed)	.110		
Fruits & Vegetables	Correlation Coefficient	.131	Very weak	Statistically Insignificant
	Sig (2-tailed)	.475		

Regression Analysis

- Simple Linear Regression Analysis was performed for scale variables such as Age, Farming Experience, Perceived Economic Benefits, Perceived Environmental Benefits, Perceived Ease of Use, Investment Cost, PATs & PI Usage, Computer and Phones Usage.

Table 8. Simple Regression Analysis

Ind. Variable	R Square	P Value	Beta Value
Age	.008	.629	-.003
Farming Experience	.000	.972	.000
Perceived Economic Benefits	.075	.129	.302
Perceived Environmental Benefits	.220	.007	.360
Investment Cost	.014	.513	.068
PATs & PI Usage	.054	.202	.340
Computer & Phone Usage	.109	.065	.562
PEU	.038	.283	.108

- Multiple Linear Regression Analysis was used for categorical variables such as Farm Size, Farm Income, Level of Education, Farm Region, Farm Crops, Land Tenure, Development Pressure.

Table 9. Multiple Regression Analysis

Independent Variable	R Square	P Value	Beta Value	
Level of Education	.004	.390	Diploma vs University	.200
			Diploma vs Master	-.086
			Diploma vs Doctoral	-.400
Farm Crops	.272	.202	Vegetables vs Fruits	-.330
			Vegetables vs Greenhouse	.136
			Vegetables vs Aquaponics	.136
Farm Size	.102	.559	<10 fed vs 10-50 fed	.083
			<10 fed vs 50-100	-.350
			<10 fed vs 100-300	-.125
Farm Income	.150	.338	<5000 vs Prefer not to say	.354
			<5000 vs 5-10k	.515
			<5000 vs 10-20k	.393
Land Tenure (Rented=0/Owned=1)	.000	.985	.009	
Farm Region (Lower Egypt= 0// Upper= 1)	.020	.442	-.207	
Development Pressure (Yes= 0 / No= 1)	.166	.020	-.423	

As well, outcomes of the Regression Analysis show that Perceived Environmental Benefits and Development Pressure have statistically significant effect on PATs adoption.

To summarize, results of Correlation analysis are in compliance with Regression analysis results.

According to the Inferential Analysis; Perceived Environmental Benefits was found statistically significant independent variable that affects PATs adoption as referred in table 8. Simultaneously, Development Pressure has been proved to have a significant impact on PATs adoption as indicated in table 9.

Answers to Research Questions

Based on the analysis performed in this chapter; the researcher will answer the research minor questions accordingly.

MiRQ1: Does Age have an effect on Precision Agriculture tools & technologies adoption?

According to Simple Regression Analysis performed previously; Age was found statistically insignificant towards PATs adoption with a β coefficient of -.003 and p= .629.

Although age was found significant in many of studies applied on PATs adoption (Isgin, Bilgic, Forster, & Batte, 2008; Daberkow & McBride, 1998). Nevertheless, other researchers proved that Age is an insignificant factor in their studies such as Daberkow et al., (2003), Robertson et al., (2012) and Castle et al., (2016).

As for β coefficient, the researcher concluded that for every 1 unit increase in Age, PATs adoption decreases by 0.003 unit, given that all other variables are constant.

MiRQ2 Does the Educational Level have an impact on Precision Agriculture tools & technologies adoption?

As per the Regression results, p= .390 which indicates that Educational Level is found statistically insignificant to PATs adoption. This result comes in line with Uddin, (2020) and Kolady, (2020).

Besides, according to Multiple Linear Regression results using dummy variable technique as this is considered a categorical variable; as for Beta value, Diploma Certificate was chosen to be a baseline to compare rest of the variables against it in their impact on PATs adoption. Accordingly, when Diploma was compared verses University Degree, β coefficient= .200, which means that University graduates can adopt PATs more than Diploma certificate holders by .200 unit.

Further, when Master degree was compared verses Diploma Certificate β coefficient= -.086, which indicates that Master degree holders are less than Diploma holders in adopting PATs by .086 unit, considering that all other variables are constant.

Additionally, when Doctoral degree was compared to Diploma Certificate β coefficient= -.400, which means that Doctoral degree holders are less than Diploma certificate holders in adopting PATs by .400 unit, taking into account, that rest of the variables are constant.

MiRQ4: Does farm size influence Precision Agriculture tools & technologies adoption decision?

Regression analysis results show that Farm Size is statistically insignificant as p value= .559. This result is contradicting with literature as economies of scale play an essential role in adopting high-end and capital-intensive tools (Kolady, Sluis, Uddin, & Deutz, 2020). Particularly, Tey & Brindal (2012), in their systematic literature review, they stipulated that in a massive number of researches, it was found that PATs are commonly adopted by large size farms to spread investment cost and uncertainty on lager size of farmlands (Walton, et al., 2008; Tey & Brindal, 2012; Robertson, et al., 2012).

Despite having this contradiction with this research result, the researcher concluded that this happened due to the small sample size. As stated by Button K. et al., (2013); that small sample size weakens the likelihood of discovering a real effect and lessen the ability of having a powerful statistical level in a scientific research. However; because of the pandemic Corona Virus, the researcher could have collected data physically by making site visits as it is more powerful than using WhatsApp or other Social Media Channels and thus, a larger sample size would have been collected.

However; Paustian and Theuvsen (2017) proved that farm size is statistically insignificant with sample size of 227 farms in a study applied in Germany.

As well, Farm Size is a categorical variable in this study, consequently, Multiple Linear Regression analysis was performed to get insightful results about relations between the groups.

The researcher assigned the group “Less than 10 feddans” as a baseline. Hence, when group “10-50 fed” is compared verses the baseline β coefficient= .083, which indicates that farms that are 10 to 50 fed. can adopt more PATs than less 10 fed. farms by .083 unit, bearing in mind that all other variables are constant.

Moreover, when 50-100 fed is compared to less than 10 def group, β coefficient= -.350, which means that farms that are 50-100 fed are less than farms of less than 10 fed in adopting PATs by .350 unit, when all other variables are constant.

Also, when “100-300 fed” is compared to “less than 10 fed”, β coefficient= -.125, which indicates that farms that of 100-300 fed. are less than farms of less than 10 fed. in adopting PATs by .125 unit, bearing in mind that rest of the variables are constant.

Lastly, when group “greater than 300” is compare to “less than 10 fed.”, β coefficient= -.019. This means that farms that are greater than 300 fed. are less than farms that are less than 10 fed. in adopting PATs by .019 unit, considering all other variables are constant.

MiRQ5: Does land tenure status affect Precision Agriculture tools & technologies adoption decision?

According the Regression Analysis, p= .958 which means that Land Tenure is statically insignificant variable to PATs adoption. This result comes in line with Isgin et al., (2008) and Roberts et al., (2002).

What's more, according to Multiple Regression analysis result, this variable was considered as categorical variable accordingly, the researcher used the dummy variable method as follows; Rented lands= 0 and Owned lands= 1. β coefficient= .009. This means that farmers who own the land are more than farmers who have rented lands in adopting PATs by .009 unit, assuming that all other variables are constant.

MiRQ6: Do farm crops have an effect on Precision Agriculture tools & technologies adoption decision?

As per Farm Crops, p= .202 which means that it is statistically insignificant towards PATs adoption. This comes in accordance with Paustian and Theuvsen (2017).

Meanwhile, as per Multiple Regression test which was performed by using dummy variable method because it is considered a categorical variable, the researcher assigned Vegetables as a baseline variable and compared rest of the groups against it regarding PATs adoption.

When Fruits group is compared Vegetables; β coefficient= -.330 which means that farms that plant fruits are less than farms that plant vegetables in adopting PATs by .330 unit, when all other variables are constant.

Additionally, Greenhouse farms against Vegetables has β coefficient value of .136, which indicates that greenhouse farms can adopt more PATs than vegetables farms by .136 unit, considering all other variables are constant. Same results with same β coefficient value were found regarding Aquaponics farms.

Furthermore, β coefficient of Medicinal and Aromatic farms when compared to Vegetables farms is -.364, which means that Medicinal and Aromatic farms are less than Vegetables farms in adopting PATs by .364 unit, when all other variables are constant.

As well, Sugar Beat farms has β coefficient= -.864 when it is compared to Vegetables farms. This means that Sugar Beat farms are less than Vegetables farms in adopting PATs by .864 unit, when all other variables are constant.

At last, farms that plant mix of Fruits and Vegetables have β coefficient= .136 when compared to Vegetables farms, which indicates that Fruits and Vegetables farms can adopt more PATs than farms that plant Vegetables only by .136 unit, if rest of the variables are constant.

MiRQ7: To what extent perceived economic benefits influence Precision Agriculture tools & technologies adoption decision?

As per the Simple Linear Regression analysis; p= .129, which means that Perceived Economical Benefits is statistically insignificant. This comes in consistency with Larson et al., (2008) and Robert et al., (2002). Although it is contradicting with Kolady et al., (2020).

As for β coefficient value; complies that for every 1unit change in Perceived Economic Benefits, PATs adoption will change by .302 unit, given that all other independent variables are constant.

MiRQ8: To what extent perceived environmental benefits influence Precision Agriculture tools & technologies adoption decision?

According to the Regression analysis; Perceived Environmental Benefits is statistically significant as p= .007. This result is aligned with Kolady et al., (2020) and Blasch et al., (2020).

In addition, β coefficient= .360 which indicates that for every 1unit change in Perceived Environmental Benefits PATs adoption will change by .360 unit, given that all other variables are constant.

MiRQ9: Does farm income have an effect on Precision Agriculture tools & technologies adoption?

According to the Multiple Regression analysis; p= .338 which indicates that Farm Income is statistically insignificant. This result comes in accordance with Castle et al., (2016).

Besides, this variable is considered a categorical variable, thus; it was divided into groups and the researcher followed the dummy variable method. Therefore, "less than 5,000 EGP/fed" group was set as a baseline and when it is compared to "5-10K EGP/fed) β coefficient= .667, which means that farms with income of 5-10K are more than farms of less than 5K EGP/fed in adopting PATs by .667 unit, considering that all other variables are constant.

Further, when it is compared with farms of 10-20K EGP/fed as income, β coefficient= .417 which indicates that farms of 10-20K are more than farms of less than 5K income in adopting PATs by .417 unit, when all other variables are constant.

Additionally, when "less than 5K" is compared with "greater than 50K"; β coefficient= .467, thus, it is concluded that farms that have income of more than 50K are more than farms of less than 5K in adopting PATs by .467 unit, considering rest of the independent variables are constant.

Likewise, when "less than 5K" is compared to the group who chose "Prefer not to say" it was found that β coefficient= .306, which means that the group who chose "prefer not to say their farm income" is more than the group of less than 5K in adopting PATs by .306 unit, when all of the variables are constant.

MiRQ10: Does investment cost have an impact on Precision Agriculture tools & technologies adoption?

As per Regression Analysis results, Investment Cost was found statistically insignificant as p= .513. Meanwhile, β coefficient= .068, which means that for every 1unit change in Investment Cost, PATs adoption changes by .068 unit, given that all other variables are constant. These results are contradicting with Keskin and Sekerli (2016) and Feder et al., 1985. This may be due to the small sample size.

MiRQ11: Does using any of PATs or PI technologies have an effect on Precision Agriculture tools & technologies adoption?

According to Simple Linear Regression analysis, p= .202 which means that PATs and PI Usage is statistically insignificant. The β coefficient= .340 which means that for every 1unit change in PATs and PI Usage PATs adoption changes by .340 unit, when rest of the variables are constant. However; these results are contradicting to Tey & Brindal (2012)' review and assumptions.

This variable was included in the study to indicate the level of knowledge to give a sense of willingness to accept development in PATs usage by integrating information intensive technological facilities. By having these results, the researcher can conclude that it is not necessary to have previous exposure to these technologies.

MiRQ12: Does using computer and smart phone have an impact on Precision Agriculture tools & technologies adoption?

According to Simple Linear Regression results, Computer and Smart Phones Usage was found statistically insignificant with p value= .065. These findings are not in line with Isgin et al., (2008) and Kolady et al., (2020).

On the other hand, β coefficient= .562 which means that for every 1unit change in this variable, will cause variations in PATs by .562 unit, given that all the variables are constant.

The researcher proclaims that if the size sample is bigger; this variable will be statistically significant, especially that p value is very close to .05.

MiRQ13: Does perceived ease of use have an influential effect on Precision Agriculture tools & technologies adoption?

According to Simple Linear Regression results; PEU has no statistical effect on PATs adoption as p= .283 which means that PEU is statistically insignificant in this model. This result comes in line with Adrian et al., (2005), nonetheless, contradicts results of Aubert et al., (2012).

As for β coefficient value of PEU, it indicates that for every 1unit change in PEU, PATs adoption changes by .108 unit, when rest of the variables in the model are held constant.

MiRQ14: Does farm region have an impact on Precision Agriculture tools & technologies adoption?

Results show that this variable is statistically insignificant as p=.442, accordingly, farm region does not predict PATs adoption. This result comes in accordance with Paustian and Theuvsen (2017) and Groher et al., (2020). Meanwhile, this is incongruent with D' Emden et al., (2006).

In this categorical variable, dummy variable method was followed in order to test the effect on the dependent variable. Multiple Linear Regression results show that farms that are located in Upper Egypt are less than farm that are located in Lower Egypt by .207 unit.

MiRQ15: Does development pressure have an impact on Precision Agriculture tools & technologies adoption?

According to results of Multiple Linear Regression Analysis; Development Pressure was found statistically significant as p= .020.

Moreover, the researcher used dummy variable method to measure the effect of this categorical variable by making Yes= 0 and No= 1. Consequently, respondents who answered No are less that respondents who said Yes in adopting PATs by .423 unit, as β coefficient= -.423, assuming that rest of the variables are constant.

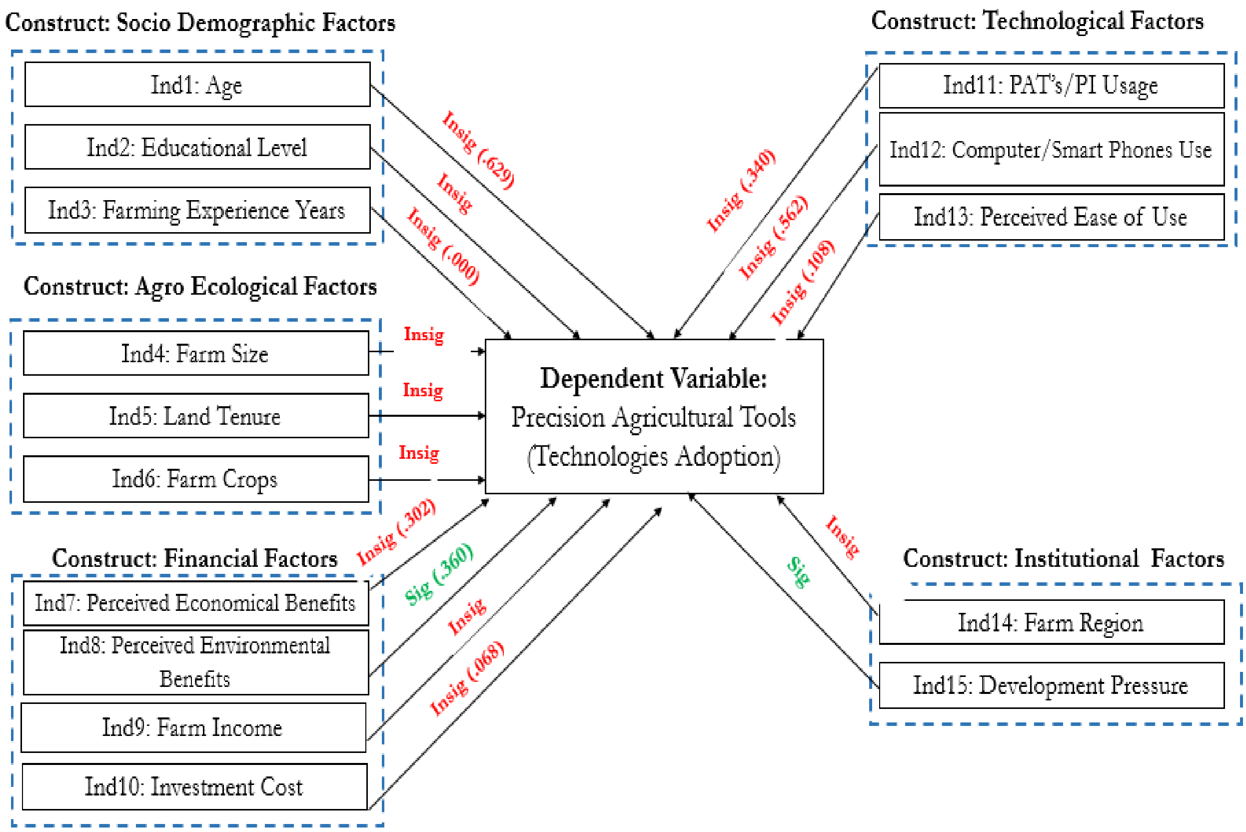

Figure 8. Results of Regression Analysis

It is concluded from Correlation and Regression analysis results that Perceived Environmental Benefits and Development Pressure have statistically significant impact on PATs adoption.

5. Conclusion

According to the results of this study; Perceived Environmental Benefits and Development Pressure are statistically significant factors on adopting PATs; therefore, the researcher may suggest the following recommendations;

- The Egyptian Government and policy makers in the agricultural sector may find these results of interest in order to encourage the Egyptian farmers to adopt more PATs by creating incentive regulations and programs stressing on implementing PATs.
- Service providers, PATs producers and sellers may find these results beneficial, as well. They can stress on the environmental benefits of PATs because this study proves that stressing on environmental benefits should enhance PATs adoption.
- With regards to the importance of the social influence; service provider may approach farms that are located at the same area of farms that employed PATs.

6. Limitations and Future Research

In fact, the selected sample is not representative of the population “Egyptian farmers”. As well, sample size was relatively small to have a powerful statistical level in the inferential analysis. In the same regard, like most of the survey-based researches; the data provided by the participants might not be accurately describing the real situation. Therefore, an expanded sample size could shed more light on other determinant variables on PATs adoption. By the same token, other methodologies could be approached in the same topic to detect adoption density or trends in Egypt or specific regions such as Lower Egypt and Upper Egypt or studying factors causing differences between smaller districts.

Besides, this study is limited to some of PATs that are directly connected to irrigation and fertilizers application to reflect on the research problem regarding water scarcity and other environmental issues caused by agriculture. Thereupon, future researches may tackle in their studies other PATs such as Yield Monitoring, Autosteering Machinery… etc.

Additionally, future research may include studying effect of applying governmental policies and regulations on PATs adoption. Moreover, future researches may address factors affecting information intensive PATs adoption to know the potential of turning all farming practices into more digitized application. Simultaneously, researchers may study what hinders Egyptian farmers from turning to high-end automated systems.

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