

UNIVERSITY OF CAPE COAST

AN EVALUATION OF THE ACCEPTANCE OF DRONE TECHNOLOGY
SERVICES FOR CONTROL OF FALL ARMYWORM IN NORTHERN

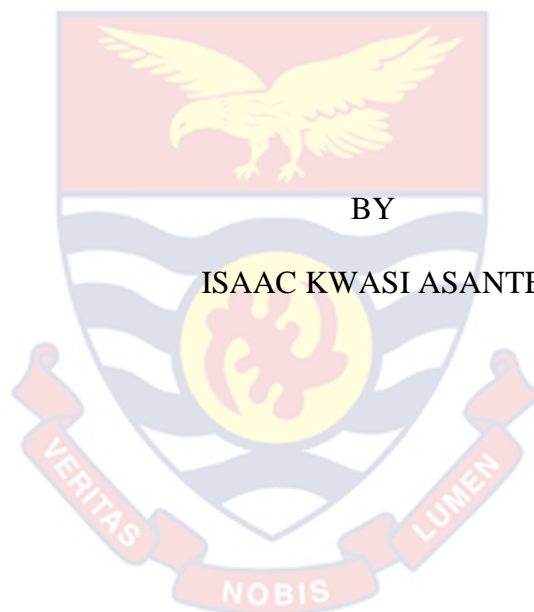


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UNIVERSITY OF CAPE COAST

AN EVALUATION OF THE ACCEPTANCE OF DRONE TECHNOLOGY
SERVICES FOR CONTROL OF FALL ARMYWORM IN NORTHERN
GHANA



Thesis submitted to the Department of Agricultural Economics and Extension
of the School of Agriculture, College of Agriculture and Natural Sciences,
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Award of Doctor of Philosophy Degree in Agricultural Extension

SEPTEMBER 2021

DECLARATION

Candidate's Declaration

I hereby declare that this thesis is the result of my own original research and that no part of it has been presented for another degree in this university or elsewhere.

Candidate's Signature Date

Name: Isaac Kwasi Asante

Supervisors' Declaration

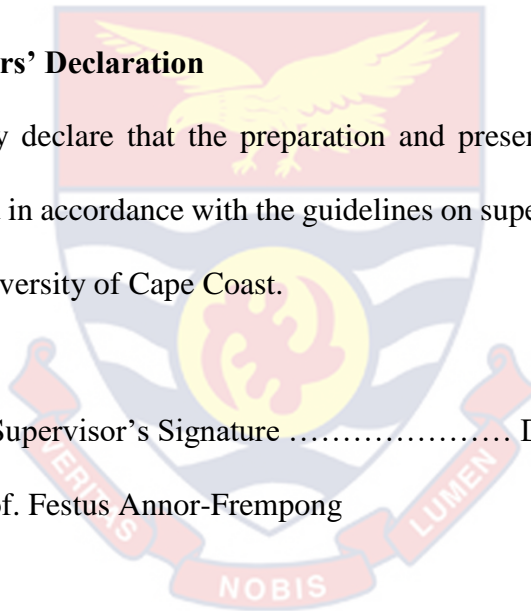
We hereby declare that the preparation and presentation of this thesis were supervised in accordance with the guidelines on supervision of thesis laid down by the University of Cape Coast.

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Name: Dr. Martin Bosompem



ABSTRACT

Modern technologies have demonstrated the potential to significantly boost agricultural production. The use of drones in agriculture has been popular in recent years because it enhances existing rudimentary tools and practices in agricultural fields. The use of drone for control of the Fall Armyworm (FAW), which has drawn international attention due to its highly destructive nature in destroying many major crops, especially maize, is not popular. To this end, the Technical Centre for Agriculture (CTA) supported a collaborative research project to examine the efficacy of a synthetic chemical for FAW control using drone in three selected districts in Northern Ghana. After the project little is, however, known about how farmers are willing to accept drone technology for control of FAW. This study sought to examine the acceptance of drone technology services for control of FAW among maize farmers in the selected districts in Northern Ghana. Adopting the mixed methods approach to collect quantitative and qualitative primary data from 150 maize farmers in the study area, measures of central tendencies, chi-square, paired sample t-test, OLS regression and PLS-SEM were utilized to analyze the quantitative data whilst thematic analysis was used to analyze the qualitative data. The results showed that, perceived usefulness, ease of use, attitude towards use and subjective norm accounted for 67% of farmers' intention to adopt the technology for control of FAW. The Ministry of Food and Agriculture and its stakeholders should work on improving the attitude of farmers towards the utilization of drone technology for control of FAW through field demonstrations where the usefulness and ease of use of the technology can be observed by the farmers and their significant associates who influence the intention of the farmers to adopt the technology.

KEY WORDS

Acceptance

Fall Armyworms

Drone Technology

Maize Farmers

Northern Ghana

Extended Technology Acceptance Model (TAM3)



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DEDICATION

To my maternal and paternal grandmothers, Angelina Awo Gyatowa Sam and
Grace Yaa Adu



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LIST OF ACRONYMS

ACP	African, Caribbean and Pacific Group of States
ANOVA	Analysis of Variance
BCR	Benefit-Cost-Ratio
CANS	College of Agriculture and Natural Sciences
CB-SEM	Covariate Based- Structural Equation Modeling
CTA	Technical Centre for Agricultural and Rural Co-operation
DAEE	Department of Agricultural Economics and Extension
EU	European Union
FAW	Fall Armyworm
FFDs	Farmer Field Days
GHS	Ghana Cedis
ICT	Information Communicatio Technology
IRB-UCC	Institutional Review Board
MoFA	Ministry of Food and Agriculture
MANOVA	Multivariate Analysis of Variance
NGOs	Non-Governmental Organizations
PCA	Principal Component Analysis
PLS	Partial Least Squares
PLS-SEM	Partial Least Squares-Structural Equation Modeling
PPEs	Personal Protective Equipments
PPRSD	Plant Protection and Regulatory Services Directorate
SARI	Savanna Agricultural Research Institute
SEM	Structural Equation Modeling

SD	Standard Deviation
TAM	Technology Acceptance Model
UASs	Unmanned Aerial Systems
UAVs	Unmanned Aerial Vehicles
UCC	University of Cape Coast



CHAPTER ONE

INTRODUCTION

Background to the Study

Agriculture is seen as one of the keys to the future development of Africa (Alliance for the Green Revolution of Africa [AGRA], 2018); many countries depend on it for economic and sustainable development (Quartey et al., 2012). The agricultural sector contributes immensely to economic growth in several ways, specifically: it provides food for an ever-increasing population, ensures food security, and supplies of sufficient raw materials (inputs) to the industrial sector. Agriculture is a main source of employment and provides a market for the products of the industrial sector, in addition to the generation of foreign exchange earnings (Ministry of Food and Agriculture [MoFA], 2015). Agriculture is the main contributor to Gross Domestic Product (GDP) of many African countries (AGRA, 2018), and in 2016, it accounted for more than 20 percent of Africa' economic output (African Development Bank [AfDB], 2018).

Africa is endowed with many resources. The bulk of world's arable land (AGRA, 2018) and more than half of the population working in the agricultural sector are found in Africa (AfDB, 2018; Nuer et al., 2018). Eze et al. (2010) have noted that the agricultural sector in Africa has a strong rural base with majority of farmers working in rural areas. Begna and Paul (2010) estimated that approximately 2.5 billion out of the 3 billion rural inhabitants in Africa are involved in agriculture with 1.5 billion and 800 million respectively, living and working in smallholder households. The agricultural sector will progressively play an essential part in improvement of low income countries where the

aggregate income and total labour force in rural areas come from the sector (Dethier & Effenberger, 2012).

Agriculture has remained the source of livelihood of most people in rural Ghana (Quarthey et al., 2012) as it accounted for 22.2% of GDP of Ghana's economy in 2017, and employed approximately 51% of the workers (Ghana Statistical Service, 2018). The sterling role of the agricultural sector to the national economy of Ghana has merited its feature in the wider national and regional policy frameworks, which when implemented effectively can improve the welfare of agricultural households through higher incomes and poverty reduction (MoFA, 2007). The importance of agriculture as the major source of food and improving livelihoods of smallholders, makes the sector an important component of development programmes aimed at poverty alleviation and enhanced food security in Africa and, for that matter, Ghana (Ogundari, 2014).

Efforts to alleviate poverty and food insecurity in developing countries like Ghana include; promotion of technological innovations in agriculture (Kebebe, 2017). This is because in the agricultural sector, new or modern technologies have demonstrated the potential to significantly boost agricultural production (Rehman et al., 2016). The USDA (2021), indicated as a result of technological advancements such as sensors, digital gadgets, machinery, and information technology, today's farms and agricultural setups are vastly different from those of a few decades ago. Agriculture currently uses advanced technologies like robotics, temperature and moisture sensors, smartphone applications, global positioning systems (GPS) technology, auto-steered and guided equipment, geographical information systems (GIS), precision soil

sampling, yield monitors, unmanned aerial vehicles and variable rate technologies on a regular basis (Kern, 2015; Van Es & Woodard, 2017).

Probst et al. (2017) argued that application of unmanned aerial vehicles (UAVs) usually referred to as “drones” in agriculture is increasingly becoming popular in recent years from its earlier application by the military for warfare in 1949 (Hanssen, 2016; Hogan et al., 2017; Magistretti & Dell’Era, 2019) to its recent deployment in fields like mining, insurance, infrastructure, media and entertainment, security and law enforcement, transport, and telecommunications (Pricewaterhouse Coopers International Limited (PwCIL), 2016). The improvement in the technology and the fall in its market price has advanced the application of drone devices for agricultural purposes (Hogan et al., 2017; Puri et al., 2017; Torres-Rua, 2017). The drone has been used to power and enhance existing rudimentary tools and methods with evidence of different applications already deployed on farms (Probst et al., 2017).

Field observation and remote characterization of agronomic factors such as soil fertility, plant diseases, water supplies, are some of the specialized drone applications in agriculture (Tsan et al., 2019). According to Puri et al. (2017) the importance of drone technology is seen in its competitive advantage to other agricultural technologies. The drone is capable of tracing illegal farm activities, surveillance of crop yields on large plantations and precise monitoring and observation of farm locations difficult to reach by humans during field fire. According to Raparelli and Bajocco (2019), drones are not limited to soil and field analysis only, but crop health assessment, crop monitoring, monitoring irrigation equipment, aerial planting, weed identification, variable-rate fertility, monitoring cattle herds, and crops spraying (Veroustraete, 2015; Probst et al.,

2017; Barbedo & Koenigkan, 2018; Ahirwar, Swarnkar, Bhukya, & Namwade, 2019).

Cognisant of the role of drones in agriculture, the African Union Commission appointed ten eminent scholars drawn from varied professional backgrounds to provide evidence-based research and recommendations that would lead to policy direction on the application of existing and emerging digital innovations like drones at the continental, regional and country levels (NEPAD, 2016). The vision of the continental body, the Africa Union (AU), on the application of drones in agriculture is to increase economic development, food production and reduce food insecurity and hunger on the continent by 2063. The resolution of the Heads of State and Government to explore the use of existing and emerging digital innovations was hinged on the adoption of the Science, Technology and Innovation Strategy for Africa (STISA, 2024) and Agenda 2063.

It is worth noting that the application of drones in Ghana is in line with the government's agricultural transformation agenda over the years. The agenda is to modernise agriculture by taking into consideration technology development and dissemination (MoFA, 2015). For instance, the Medium-term National Development Policy Framework, (the Ghana Shared Growth and Development Agenda (GSGDA) I, 2010-2013) provided the framework to accelerate the modernisation of the agricultural sector (National Development Planning Commission Ghana [NDPC], 2014). The Food and Agriculture Sector Development Policy (FASDEP II) (MoFA, 2007), the Medium-Term Agricultural Sector Investment Plan (METASIP) (MoFA, 2010, 2015) and government's flagship policy "Investing for Food and Jobs (IFJ): An agenda for

transforming Ghana's agriculture (2018-2021)" (MoFA, 2018) had technology development as its pivot. The transformation agenda of the agricultural sector is to improve agricultural productivity and economic growth based on technology (NDPC Ghana, 2010).

According to a recent report by the FAO, Fall Armyworm (FAW), which has drawn international attention due to its highly destructive nature, has spread to almost all countries in Africa, infesting and destroying many major crops, particularly maize, which is the most extensively produced main food crop in Sub-Saharan Africa (FAO, 2018). The FAO (2020) posited that the FAW *Spodoptera frugiperda* (J.E. Smith) (Lepidoptera: Noctuidae) is a moth (adult stage) with a phytophagous larva or caterpillar that feeds on more than 80 crops but with special preference for maize. Abrahams et al. (2017) noted that the pest remained in the Americas until early 2016, when it was first discovered in West and Central Africa. Since its arrival on the continent, the pest has quickly spread throughout Africa, threatening agricultural productivity and food security (Kruger, 2017).

According to CABI scientists, the destruction of maize by FAW could result in annual maize production failures of 8.3 to 20.6 million tonnes (enough food for 40.8 million people) estimated to be between USD 2.5 and 6.2 billion in 12 African maize producing countries if proper control methods are not implemented (Day et al., 2017). Mengestu (2017) added that the impact of the FAW could rise up to about 30 percent or more losses in maize production at the country level. Rwomushana et al. (2018) conducted a household survey in Ghana and estimated that maize annual yield losses in financial terms in the country due to the impact of the FAW is valued at US\$177 million. The FAO

(2020) argued that FAW infestation is most likely to trigger population displacement from rural agricultural communities to urban areas, putting millions of the world's poorest people's food security and livelihoods in jeopardy, including Ghana.

Hruska (2019) posited that the rapid spread of the pest, combined with concerns about potential yield losses, has prompted a search for long-term management solutions among scientific community and policy makers. Mengestu (2017) noted that cultural, chemical, biological, and integrated pest control are all options being used by farmers for managing the FAW. Rwomushana et al. (2018) argued that the most common method of FAW control is the application of pesticides using the knapsack sprayer. According to CTA (2019a), these control methods are not effective due to the efficacy of pesticides and the pest's nocturnal feeding behaviour and life cycle. FAO (2020) also argued that the rising use of hazardous pesticides is another key issue lined with FAW infestation, which provide farmers with limited immediate remedy and also harm humans, livestock, aquatic life and environmental health. Hence the need to explore the use of a technology that reduces yield losses and minimizes the harmful effect of synthetic pesticides on humans, livestock, aquatic life and the environment.

New reports from the African Development Bank, the FAO, and the CGIAR highlighting the benefits of digital agriculture indicate that drones are one of the most promising technologies for addressing Africa's agricultural challenges (AfDB et al., 2020a, 2020b, 2020c). Despite the benefits of drones in agriculture, the application of them for spraying pesticides for FAW control is not popular. The Technical Centre for Agricultural and Rural Cooperation

(CTA) between the African, Caribbean, and Pacific Group of States and the European Union member states (CTA) in Wageningen, the Netherlands, has been a major supporter of drone use in agriculture in Africa over the last few years (CTA, 2019b). CTA teamed up with AIRINOV, a pioneer in drone-based crop analytics, in 2017 to provide training for young drone operators from eleven ACP countries under “Transforming Africa’s Agriculture: Eyes in the Sky, Smart Techs on the Ground” programme (CTA, 2016). In 2019, at Accra, CTA, a key funding agency for UAS applications in agriculture and related sectors, supported a collaborative research project involving the Department of Agricultural Economics and Extension of the University of Cape Coast, the CSIR-Savannah Agricultural Research Institute (CSIR-SARI), Bayer CropScience of Paris, and AcquahMeyer Drone Tech Ltd. to examine the efficacy of a synthetic chemical for FAW control using drone (CTA, 2019a).

The central objective of the project was to determine the socioeconomic impact of introducing pesticides application via drone technology to the market, as well as to identify possible success factors in place of true ‘market acceptance of drone technology for pesticide application for control of FAW’. Bayer CropScience, as part of the project, provided one promising insecticide for FAW control which was undergoing registration for the demonstration plots which was established by CSIR-SARI in Kukua in the West Mamprusi Municipality in the North East Region, Nyankpala in the Tolon District and Salakpang in the Mion District in the Northern Region. AcquahMeyer supplied the spraying drone, while the Department of Agricultural Economics and Extension conducted the socio-economic research. In all, three hundred (300)

maize farmers participated in the project which was conducted in two phases (CTA, 2019a).

Phase one involved the random selection of 300 farmers from six communities within 5-10 km radius of the trial plots (50 farmers were selected from each of the six communities, namely, Kukua, Loagri, Nyankpala, Kpalsogu, Salanpkang and Kplijine who participated in a pre-drone trail survey on farmers' practice on the control of FAW. The second phase of the project involved random selection of 150 farmers (25 farmers from each of the six communities) from the previously selected 300. The 150 farmers participated in the drone and knapsack applied pesticides for control of FAW on the CSIR-SARI established trial plots in Kukua, Nyankpala and Salakpang. The farmers had the chance to witness field demonstrations by watching a video, and live observation of drone and knapsack application of pesticides for control of FAW (CTA, 2019a). This study sought to examine the acceptance of drone technology services for control of FAW by maize farmers in selected districts in Northern Ghana.

Statement of the Problem

Africa's population is growing at an alarming rate than most parts of the world. The number of people living in Sub-Saharan Africa is projected to reach 600 million by 2030, two hundred percent more than what it was in 2010 (FAO, 2012; AGRA, 2019). As the population is growing, there is the need for increased food production to support the increasing population, and Ghana is not an exception (FAO, IFAD, & WFP, 2015; FAO, IFAD, UNICEF, WFP, & WHO, 2018). Critical to the adequate supply of food for the growing population is maize production. Maize (*Zea mays L.*) is an important staple crop in the sub-

region. The crop accounts for more than 50 percent of total cereals and grains production in Ghana and mostly consumed by farm households (Abdulai, Nkegbe, & Donkoh, 2018). The crop is cultivated by predominantly smallholder farmers in all the ecological districts in the country under rain-fed production (Adu et al., 2014).

Increased agricultural production of maize is a major driver of rural food security, employment and economic growth (Jack & Tobias, 2017). The bulk of maize produced in Ghana is consumed by farm households. Wongnaa and Awunyo-Vitor (2019) noted that, an increase in the production of the crop will undoubtedly improve food security in the households and Ghana as whole. MoFA (2007) revealed in the Food and Agricultural Sector Policy document (FASDEP II) that, population pressure is heightening food demand in Ghana. The incidence of hunger in all regions of Africa is rising and this phenomenon accounts for about 20 percent of the prevalence of undernutrition globally (FAO et al., 2019). AGRA (2019) posited that the number of people living in hunger on the African continent of which Ghana is no exception, has grown to about 34.5 million since 2016. This is attributed to climate emergency that has reduced the yield of a key crop like maize by 40 percent (AGRA, 2019).

Pimentel (2009) postulated that globally, more than three billion metric tons of crop agro-chemicals are used on annual basis. However, argued that despite the large volumes of pesticides applied annually, close to 40% of all field and harvested crops are destroyed by plant pathogens, insects, weeds and pests such as the FAW (Pimentel, 2009). It is not far reaching to note that the incidence and spread of the invasive pests such as FAW (*Spodoptera frugiperda*) since 2016, is aggravating the situation in Ghana and on the

continent (CABI, 2017a, 2017b; Hruska, 2019). Day et al. (2017) reported in a survey that the estimated national mean loss of maize in 2017 in Ghana and Zambia due to the incidence of FAW was 45 percent (range 22–67%), and 40 percent (range 25–50%) respectively. Another household survey on the severity of the incidence of FAW conducted in Ghana revealed that 98 percent of farmers reported the incidence of FAW on their maize farms (Rwomushana et al., 2018). The FAW is a native pest to the tropical and sub-tropical America regions which has become an important pest of maize in the tropics of Africa, spreading to almost all countries on the continent (Sisay et al., 2019).

The rapid spread and anxieties over possible yield losses of an important staple crop like maize have led to the search for sustainable ways of managing and controlling the pest (Hruska, 2019). The adoption of Information Communication Technologies for Agriculture (ICTs4Ag) such as Unmanned Aerial Systems (UASs) can be used to mitigate the myriad of challenges in agriculture, including pest and disease control (Rambaldi & Guerin, 2018; Soesilo & Rambaldi, 2018). For example, manned helicopters were mobilized by the Zambia Air Force (ZAF) in collaboration with the Ministry of Agriculture following an executive order to spray several high incidence locations throughout the country to control the FAW during the 2016/17 growing season. An estimated 124,000ha of maize were damaged by the pest in Zambia during that season (African Aerospace Online News Services, 2017).

The government of Ghana through its agencies such as MoFA and farmers are using several management strategies including traditional chemical control using knapsack. However, most of these control methods are ineffective because of the efficacy of pesticides, the feeding behaviour and life cycle of the

pest that is mostly nocturnal (CTA, 2019a). This has initiated the debate for the use of UAVs (Drones) for the control of the FAW (Rambaldi & Guerin, 2018; CTA, 2019a). While most of the farmers in America and other parts of the world affected by FAW are large-scale farmers, the vast majority of farmers affected by the pest in Africa are small holders (Chamberlin, 2007). Therefore, Hruska (2019) posited that, the significantly different context in Africa requires that different management options including the use of drones to control the pest must be explored. The spraying UAVs (Drones) have been used in the agricultural fields for different activities such as application of fertilizers (Ajay et al., 2017), weedicides (De Rijk et al., 2018) and pesticides (Garre & Harish, 2018).

In spite of their potential to increase yields, drones and other technologies continue to have limited development in Ghana due to high operational costs and limited availability (Bawa, 2019; Jack & Tobias, 2017). There is also limited empirical data on the use of the drone technology in Ghana especially in agriculture. In light of this, the novel CTA-funded collaborative project to examine the efficacy of a synthetic chemical application for FAW control using drone provides an option of hope. The highlights of the project are a few questions which need answers; Are farmers aware of the use of drone for agriculture? Do farmers perceive the drone services to be beneficial to them for control of FAW? Do the costs and benefits of using drone services outweigh the use of the knapsack sprayer for the control of FAW? Would the farmers accept drone services for the control of FAW in Northern Ecological zone of Ghana where the standard of living of the people is reported to be low? (Ghana Statistical Service [GSS], 2018). What is the intention of the farmers to adopt

drone services? This study among others, sought to find answers to these questions to determine the intention of the farmers to utilize drone services for control of FAW in Ghana.

General Objectives of the Study

The general objective of the study was to examine the acceptance of drone technology services for control of FAW by maize farmers in selected districts in Northern Ghana.

Specific Objectives of the Study

The specific objectives formulated for the study were to:

1. describe the awareness of farmers on the use of drone technology for agriculture in the study area.
2. examine farmers' perceived benefits of drone technology services for control of FAW in the study area.
3. compare the perceived costs and benefits of drone technology against the use of knapsack sprayer for control of FAW in the study area.
4. determine the intention of maize farmers to adopt drone technology services for control of FAW in the study area.
5. examine the determinants of farmers' intention to accept drone technology services for control of FAW in the study area.

Research Questions of the Study

In order to achieve the objectives of the study, the following research questions were formulated;

1. What is the awareness of the farmers on the use of drone technology for agriculture?

2. What is the perception of the farmers on the benefits of drone technology services for control of FAW in the study area?
3. What are the costs and benefits of using drone technology services to the use of the knapsack sprayer for the control of FAW from the perspective of farmers in the study area?
4. What is the behavioural intention of maize farmers in adopting drone technology services for the control of FAW in the study area?
5. What are the determinants of farmers' intention to accept drone technology services for control of FAW in the study area?

Hypotheses of the Study

The following hypotheses were formulated based on the objectives of the study;

1. H_0 : the farmers in the three districts were not related in their awareness of drone technology for agriculture in the study area.
2. H_0 : the farmers did not differ significantly in their perception of the benefits of drone technology for control of FAW after video and live drone applications of pesticides.
3. H_0 : there was no set of principal factors that represented the underlying perception of farmers on the benefits of drone technology for the control of FAW.
4. H_0 : the maize farmers in the three districts did not differ on the optimal linear combination of the principal factors underlying their perception of the benefits of drone technology for control of FAW.
5. H_0 : the farmers did not differ significantly in their perceptions about the costs and benefits of using drone technology against the use of the knapsack sprayer for the control of FAW.

Significance of the Study

The use of UAVs in agriculture is growing. Many enterprises in Ghana are likely to offer soil analysis, crop health assessment, monitoring, spraying, planting, weed identification and yield estimation services to farmers. However, it is important for the end users (farmers) to participate in the development of technologies to offer such services so as to ensure acceptance and effective usage. The study has provided background characteristics that predict the acceptance of drone technology for control of FAW. Service providers of drone technology can use the study to identify categories of farmers who are most likely to accept and use drones to perform crop related services, especially for the control FAW on farms.

The Ministry of Food and Agriculture (MoFA) can use the results to develop programmes, strategies, and intervention to combat the menace caused by FAW in Ghana using drone technology at the policy formulation level. The Departments of Agriculture such as DADU and MADU can use the data to initiate programme to improve the use of digital technologies by farmers in Ghana. The result on the economic costs and benefits of drone technology services for the control of FAW would help farmers to consider costs and benefits of using drone technology services when deciding whether to adopt drones for the control of FAW on farms.

The study is anticipated to add to the body of knowledge on drone technology for pesticides application and the extended technology acceptance model in the Northern part of Ghana, the first of its kind in the sub-region. The results on the perceived benefits of drone technology for control of FAW provided a measurement construct for measuring perceived benefits of drone

technology in Ghana in particular, and Africa as a whole. The outcomes of the study would not only be beneficial to the candidate but other stakeholders like Bayer Crop Science, Acquahmeyer Drone Tech, the Ministry of Food and Agriculture, the Departments of Agriculture in the Tolon, Mion and West Mamprusi districts, farmers, NGOs and academic scholars interested in the development of agriculture.

Variables of the Study

The study considered both dependent and independent variables. The dependent variables were variables such as perceived usefulness, perceived ease of use, attitude towards the use and the behavioural intention to adopt drone services by farmers in the Northern part of Ghana. The independent variables included computer self-efficacy, perceptions of external control, subjective norms, image, job relevance, output quality, result demonstrability, computer anxiety, computer playfulness, computer enjoyment, experience and volunteriness. Other independent variables considered were farmers' perceived benefits of drone technology services, perceived economic costs and benefits of drone and the socio-demographic characteristics of farmers (sex, age, level of education, years of farming experience, marital status, farm size, yield of maize, and income from the maize sales, etc.).

Delimitation of the Study

Delimitation seeks to describe the scope or establish the boundaries of the study in order to make it handy, manageable, optimal and smart (Baron, 2009; Akanle, Ademuson, & Shittu, 2020). According to Theofanidis and Fountouki (2018), a study can be delimited in the study population, objectives, research questions, theoretical background and the variables under-study. The

study focused on the Northern and North East regions in Northern Ghana. The two regions are regarded among the high maize producing regions in Ghana (MoFA, 2017). Three districts were selected from the regions, namely: Tolon and Mion Districts in the Northern Region and West Mamprusi Municipality in the North East Region. The districts were selected based on the ecological diversity (Baidoo et al., 2016; Bawa, 2019). Six communities were selected from the three districts, two in each district (Salanpkang and Kplijine in the Mion District, Nyankpala and Kpalsogu in the Tolon District, and Kukua and Loagri in the West Mamprusi Municipality).

Many factors such as high initial and maintenance cost, pesticides drift, environmental and organisms exposure to pesticides influence the perceived costs and benefits of technology (Ahrwar et al., 2019; Faiçal et al., 2017; Lou et al., 2018; Mogili & Deepak, 2018). The study on the costs and benefits was delimited to the perceived economic costs and benefits and not financial since the study evaluated farmers' perception on drone technology services and not acquiring the technology devices to use. The study on the TAM 3 variables did not consider 'objective usability' which focuses on users of technology being allowed to use the technology to compare the time used to complete a predetermined task to that of an expert using the same technology to complete a similar task.

Flying a drone requires a trained pilot with a permit. Farmers were not trained pilots and could not be trained taking into consideration the cost and time of training. Objective usability measure therefore was eliminated from the study. The experience variable used with the TAM 3 is the number of years of farming experience of farmers. This is because all the farmers had the

opportunity to experience by observing the spraying drone on the field for the same number of times. Therefore, number of years of farming experience was used with the TAM 3 variables to test its moderating effect in the model. Furthermore, the study is delimited to opinions formed by farmers who participated in the field experimental field activities during spraying of pesticides using drone technology. Any other experiences of the farmers with drones were not considered in this study.

Limitations of the Study

The limitations are factors often out of control of the researcher, factors that may affect the results of the study or the interpretation of the findings (Baron, 2009) and the methodology in some ways (Akanle et al., 2020). According to Theofanidis and Fountouki (2018), limitations are closely associated with the design, statistical model constraints and other factors such as sampling. The use of enumerators for data collection could have posed a challenge inter rater validity. The enumerators interpreted the questions on the structured interview schedule into local languages (Dagbani and Mampruli) for understanding of the respondents. Inaccurate interpretation of the questions may have affected the results of the study.

Due to the sample size of 150 maize farmers, the findings of the study may not be generalized beyond the population of farmers sampled for the study (Baron, 2009). Data collection was done on four different occasions. A significant number of the 150 maize farmers selected during the preliminary survey were not available during the second pesticides application with the drone. Only 105 farmers participated in the second pesticides application using the drone technology resulting in a response rate of 70%. However, according

to Baruch and Holtom (2008), the minimum response rate for a survey using primary data from individuals is approximately 53%, signifying that the response rate of the maize farmers during the second pesticides application was valid.

Assumptions of the Study

The structure interview schedule and focus group discussion guide are cost-effective and the most appropriate methods for collecting data for a study of this nature (mixed method study). It is assumed that the variables of interest were normally distributed in the population. It is also assumed that respondents were fair, honest and willingly provided relevant information for the study. The study assumed that all respondents provided sincere responses to the questions presented in the structure interview schedule and focus group discussion guide. Furthermore, it is assumed that the respondents were able to assess awareness of drone technology, perception of the costs and benefits of drone technology for control of FAW, and acceptance of the technology for control of FAW in the Northern part of Ghana.

Operational Definitions of Terms for the Study

The following terms were operationalized for the study:

Acceptance: The farmers' willingness to accept the true situation of adopting drone services for control of FAW in Northern Ghana.

Awareness: Whether famers have seen or heard of drone technology for agriculture.

Behavioural intention: The desire, propensity, tendency, proclivity, inclination, and predisposition of the farmers to accept or adopt the drone services for spraying pesticides to control FAW.

Control: The farmers' efforts to effectively manage the occurrence of FAW in their fields.

Drone technology: A pilotless aircraft that is piloted remotely and deployed for spraying pesticides to control FAW in agricultural fields.

Fall Armyworm (*Spodoptera frugiperda*): A lepidopteran pest that feeds on the leaves and stems of over 80 different plant species, wreaking havoc on maize crops in the study area.

Maize Farmers: Individuals from the selected districts cultivating maize as a staple crop.

Perceived benefits: The perception of positive results induced by the farmers' acceptance of drone for control of FAW in Northern Ghana.

Perceived Costs and Benefits: The perception of the farmers after assessing the strengths and weaknesses of the drone and the knapsack sprayer in order to determine which one provides economic benefits for FAW control.

Organization of the Study

This study was organized into ten chapters. Chapter One set the study into perspective by providing the background to the study, statement of the problem, objectives of the study, the research questions and the hypotheses of the study. The significance of the study, variables of the study, delimitations, limitations, assumptions, operational definitions and organization of the study are all provided in this chapter. Chapter Two reviewed literature on theories, and variables related to the study. The Diffusion of Innovation (DOI), the Theory of Reasoned Action (TRA), the Theory of Planned Behaviour (TPB) and the Technology Acceptance Model (TAM) were reviewed. The state of agriculture in Ghana, precision agriculture, application of drones in agriculture, the benefits

and costs of drones in agriculture. Other topics reviewed were maize production, pest of maize and control of FAW in maize production and background characteristics of maize farmers. The chapter ended with the conceptual framework that guided the study.

Chapter Three focuses on the methodology devoted to description of the study area, philosophical underpinnings of the study, the research approach (paradigm), research design, population, sample and sampling procedure, instrumentation, data collection, data analysis procedure and ethical considerations. Chapter Four was organized into the background and farm-related characteristics of the farmers. Chapters Five looked at the level of awareness of the farmers on the use of drone technology in agriculture. Also, Chapters Six and Seven were organized into the perceived benefits, and the costs and benefits of using drone as an alternative to the knapsack sprayer. Chapters Eight and Nine covered the intention of the maize farmers to accept or adopt drone services for control of FAW, and the background and farm-related characteristics which informed their intention. The Final Chapter covered the summary, conclusions and recommendations based on the specific objectives of the study.

CHAPTER TWO

LITERATURE REVIEW

Introduction

This chapter reviewed literature linked to the acceptance of drone technology services for the control of FAW in selected districts in Northern and North East regions of Northern Ghana. The theoretical frameworks that underpinned the research, concepts related to drone technology and FAW were reviewed. The chapter ends with empirical review and conceptual framework derived from the parameters that guided the study.

Theoretical Framework

According to Cohen, Manion and Morrison (2007), theory is a rational ediface formulated by scientists that provide explanation to human behaviour. The use of theoretical frameworks in research is to limit the scope of the study by focusing on specific variables to be analysed and interpreted based on given definitions and creating knowledge by confirming or challenging theoretical assumptions (Neuman, 2014; Singh, 2006). The study adopted three theoretical frameworks and one model namely; Diffusion of Innovation Theory (DOI) by Everett Rogers (1995, 2003), the Theory of Reasoned Action (TRA) by Martin Fishbein and Icek Azjen (1975), the Theory of Planned Behaviour (TPB) by Icek Azjen (1985) and the Technology Acceptance Model (TAM) by Fred Davis (1989).

Diffusion of Innovation Theory

The study was guided by the diffusion of innovation theory developed in 1962 by Everett Rogers (1995). The theory is regarded as one of the oldest theories in social science. The choice of the Diffusion of Innovation Theory was

informed by its provision of the framework that explains the process by which an innovation diffuse through communication channels across different populations. The theory originated in communication, formulated to predict how, over time, an innovation or a product gains momentum and spreads through a particular social system or a population (Noel et al., 2019). The Diffusion of Innovation Theory established the foundation for conducting research on innovation acceptance and adoption (Lai, 2017).

The theory states that diffusion is the social process by which an innovation or a new idea or a product is communicated to people in a social system through channels over time (Rogers, 2003). Four key words come up strongly in the definition. These are 'innovation', 'communication channels', 'time' and 'social system'. Hawkins and Mothersbaugh (2010) defined innovation as "an idea, practice, or product perceived to be new by relevant individuals or groups" (p. 248). Rogers (2003) emphasized the importance of the perception of newness of the innovation when discussing the diffusion of innovation. In reality, not all innovations, ideas, practices or products are new; they must, however, be perceived as novel. The innovations are spread through communication channels.

According to Rogers (2003), communication channels are the means by which information or messages are moved from one individual to another. Rogers identified two distinct channels through which innovations are diffused; mass media and interpersonal channels (Valente et al., 2015). While the mass media disseminate information such as news or educational messages on innovations, interpersonal channels transmit information between individuals and permit exchanges between them (Xiong et al., 2016). Furthermore, while

the initial importance of mass media is to raise awareness about innovations, interpersonal networks become more important over time as people turn to their peers for views and assessments of new ideas (Raynard, 2017).

Time is also an essential aspect of diffusion: a mechanism that unfolds over time is diffusion (Rogers, 2003). Therefore, when examining how a person or other adoption unit gradually changes its internal state (e.g. information or decision to adopt) and open actions, Valente et al. (2015) stated that time is important to actual adoption or rejection of the innovation. Similarly, time is a significant metric when categorizing adopters into various groups or evaluating the rate of adoption of an innovation – the number of adopters in a given period for an innovation (Rogers, 2003). Finally, diffusion of innovations often occurs in a social system.

According to Hawkins and Mothersbaugh (2010), a social system is defined as “a series of interrelated units engaged in joint problem solving to achieve a common objective” (p. 248). Individuals, informal groups, organisations, and/or subsystems may be the participants or units of a social system (Ball et al., 2014; Rogers, 2003). Therefore, adoption of an innovation does not occur concurrently in a social system; rather it is a process whereby some individuals are more likely to adopt the innovation than others (Rogers, 1995). Adoption indicates that an individual does something different from what they had done previously, such as buying or using a new product, acquiring and executing a new behaviour (Rogers, 2003). Fundamental to adoption is that the individual must perceive the innovation, idea, behaviour, or product as novel or innovative (Alomary & Woollard, 2015). It is through this process that diffusion of the innovation is possible (Lai, 2017).

Rogers (1995) posited that adoption of innovation occurs after having gone through five stages including, ‘understanding’, ‘persuasion’, ‘decision’, ‘implementation’, and ‘confirmation’. Rogers (2003) noted that a future adopter going through the innovation-decision process is assisted by the passive or active consumption of information and how-to knowledge, peer reviews and personal experience. This decreases the ambiguity associated with the idea or product viewed as new by steadily improving perception of the innovation (Rogers et al., 2019). In the decision process, each stage has the potential for the person to reject innovation by forgetting it after the stage of knowledge or simply by not acting on their positive attitude to innovation (Ball et al., 2014). This phenomenon leads to what is known as the ‘knowledge-attitude-practice gap (KAP-gap)’.

According to Bongaarts (1991), knowledge-attitude-practice gap (KAP-gap) outlines the situation in which people have acquired understanding and knowledge of an innovation, have built a positive attitude towards it, but do not act on it. This often arises in preventive innovations: those that can avoid or reduce an undesirable future occurrence. Since the impact of embracing innovation is a “non-event,” something that does not happen, access to the advantages of innovation does not seem to be an urgent problem, even though the overall attitude towards innovation is optimistic (Singh, Singh, & Verma, 2016). Yar’Zever and Rabiou (2019) indicated that the cost of modifying one’s actions is often non-zero, that is, the person would not want to bear the cost if he/she is not motivated enough to make the change.

Rogers (2003) outlines many strategies to help an innovation reaching its target audience, such as when an innovation introduced to a social network

is embraced by a high profile individual and generates an instinctive demand for the innovation (Rogers et al., 2019). The principles of diffusion can be used in ways that promote the dissemination of innovations, especially in low-resource societies, a technique known as purposive dissemination or designing for diffusion (Dearing & Cox, 2018). Rogers uses an “innovativeness” metric to identify various groups of adopters which occasioned the development of S-shaped adoption curve of innovators, early adopters, early majority, late majority and laggards (Rogers, 2003). Social interactions such as peer effect, interdependence preference, social learning, imitation, neighbourhood effect, social effect and conformation influence the adoption process (Xiong et al., 2016). Rogers (1995) identified five attributes of an innovation such as ‘relative advantage’, ‘complexibility’, ‘compatibility’, ‘observability’, and ‘trialability’ which affect the adoption of innovations.

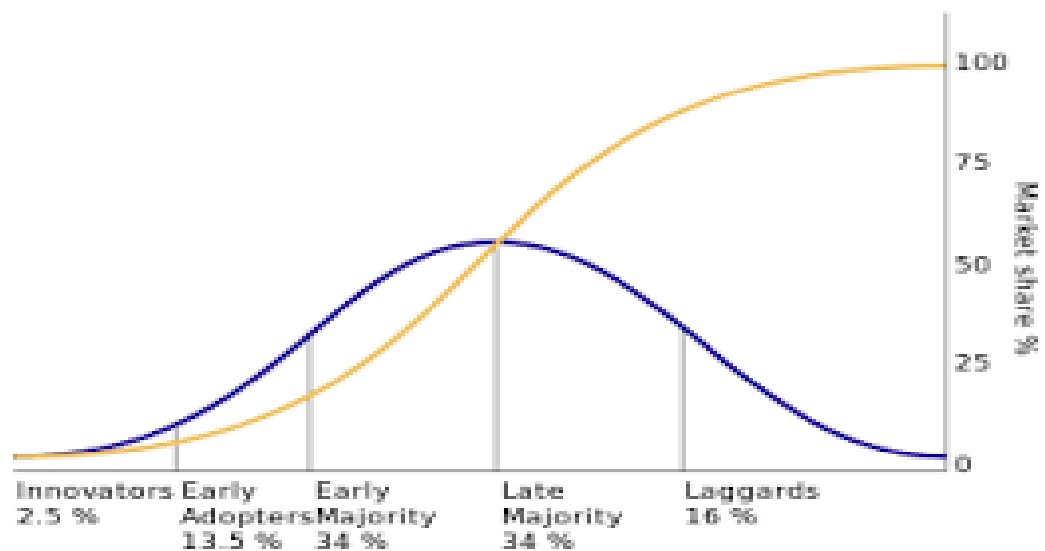


Figure 1: Rogers' Categorization of Adopters

Source: Rogers (2003)

The Diffusion of Innovation Theory has many limitations published in literature. Bayer and Melone (1989) posited that limitations of the theory of diffusion include the failure of the theory to:

1. provide specific conceptual and operational definitions of adoption;
2. distinguish between an innovation's acquisition/ authorization at the organizational level and its adoption at the individual, user level;
3. give theoretical reasoning and empirical support for the five adopter categories' application in ex ante classification;
4. incorporate discontinuity (stopping adoption) into the theory's existing specification;
5. specify the impact of mandates on diffusion and adoption in theory;
6. substantiate the causal links inferred but not explicitly stated in the theory through appropriate study methodologies; and,
7. consider interactions between various social systems (p. 164).

Lyytinen and Damsgaard (2001) in the critique of the theory posited that;

1. echnologies are unique packages created by independent and unbiased innovators;
2. the diffusion arena, which is separate from the invention locality, is where technologies diffuse in a homogeneous fixed social context;
3. iffusion rate is a function of push and pull forces; push variables include technological features and communication channels, while pull is driven by rational choices made by adopters;
4. adoption decisions are based on the information available, preference functions, and characteristics of the adopters;

5. diffusion occurs through several stages, each of which has little or no input; and
6. the time scales are brief, and the dissemination history is not important. (p.7).

LaMorte (2019) synthesizing the limitations of the theory posited that:

1. the categories of adopters, for example, did not originate in agricultural extension and were not established to directly refer to the adoption of new behaviours in extension;
2. the theory does not encourage the implementation of extension programmes in a participatory manner;
3. the theory is more appropriate for behavioural adoption than abstinence or behavioural prevention.
4. the adoption of new behaviors is unaffected by a person's income or social support (or innovation) (para. 6).

Despite the limitations, the Diffusion of Innovation Theory has been used extensively in literature. A number of researches have been published focusing on diffusion of innovation and adoption of information technologies at the organizational and individual levels (Khurshid et al., 2018; Talukder et al., 2019; Wang & Lo, 2016). At the organizational level, Wang and Lo (2016) found out that the intention of adoption of open government data was statistically predicted by relative advantage and compatibility. Also, Talukder et al. (2019) in a research on potential determinants of adoption of big data within organizations found competitive advantages as the most important factor adopting the theory. At the individual level, Khurshid et al. (2018) examined the predictors of open data usability and found relative advantage, compatibility

and observability as significant predictors of adoption of open data information systems by citizens.

This present study examined the acceptance of drone technology services for pesticides application for control of FAW by maize farmers in Northern Ghana. The Diffusion of Innovation Theory was adopted because it provides a comprehensive and systematic framework for research on diffusion of innovation and adoption of technologies such as drone technology in a social system. The five characteristics of an innovation namely: 'relative advantage', 'compatibility', 'complexibility', 'trialbility' and 'observability' provided the anchor for measuring the perceived ease of use and usefulness of drone technology for control of FAW. The Diffusion of Innovation Theory was used to initiate the adoption decision process by creating awareness of the drone technology services for FAW control through participatory action research process where farmers were exposed to pesticide application with the drone. The social-demographic characteristics and economic issues with the social context of the theory was also used to predict farmers' intention to adopt the drone.

The Theory of Reasoned Action (TRA)

The Theory of Reasoned Action (TRA) was developed by Icek Ajzen in 1967 and collaborated with Martin Fishbein at the beginning of the 1970s to broaden it (Fishbein & Ajzen, 1975). In the 1980s, appropriate interventions leading to human behaviour was examined utilizing TRA, and since then many researches have applied it to predict and explain computer usage behaviour (Ajzen, 1991; Ajzen & Fishbein, 1988). The theory was adopted for the study because it gives a framework for understanding the voluntary actions of maize

farmers toward the use of drone technology services for control of FAW (Doswell et al., 2011). The theory posits that, the attitude toward a particular behaviour and subjective norms regarding that behaviour collectively predict intention of the person to execute a behaviour (Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1975).

The primary aim of the TRA is to understand the voluntary actions of a person by analyzing the underlying fundamental reason for a behaviour (Doswell et al., 2011). The theoretical principles of TRA emphasize developing an observation system based on two classes of variables, which are:

1. attitudes defined as a desirable or undesirable feeling in relation to the achievement of an objective;
2. subjective norms, which are the very demonstration of the persons' observation in relation to the ability of reaching those goals with the product.

According to Staats (2004), attitude is evaluated with a sequence of adjectives (for example, good-bad, pleasant-unpleasant; desirable-undesirable) that are normally combined statistically to obtain the results of a general opinion of a certain act while subjective norm is the individual's interpretation of other people who are important to them and wants them to perform the action or not to perform it. Attitude is affective and impinges upon a group of beliefs about the object of behaviour (Lai, 2017). People who are important may differ from but will include family, friends, neighbours, religious institutions, political affiliation and environmental organizations (Staats, 2004).

The third variable which is behavioural intention, is the conscious intention to perform a behaviour (Staats, 2004). The behaviour performance by

a person is determined by the strength of the intention of the person (Doswell et al., 2011). Fishbein and Ajzen (1975) posited that intention is the result of a decision process established on the attitude and the subjective norm, and it is the determinant of behaviour. Finally, behaviour is the execution of a certain act; thus behaviour in the theory of reasoned action is typically limited to acts that others can witness, such as separating waste and purchasing organic food (Icek Ajzen & Madden, 1986).

Although the theory of reasoned action was effectively used to predict a number of behaviours, it was designed to explain voluntary behaviours (i.e., personal power to engage in the behaviour) (Fishbein & Ajzen, 1975). One of its weaknesses is that, non-volitional actions (i.e., less able to make a choice to engage in the behaviour) are not accounted for by the theory (Downs & Hausenblas, 2005). Hence the theory was expanded, Ajzen and Fishbein (1988) and Ajzen (1991) to include perceived behavioural control, which formed the planned behavior theory (TPB). The theory has also been subjected to several criticisms with the most significant criticism being that TRA is not falsifiable (Greve, 2001; Liska, 1984; Ogden, 2003). Because a good theory must be falsifiable, the Theory of Reasoned Action is not a good theory if it is not falsifiable, regardless of how many scholars believe it is valuable (Trafimow, 2009).

Despite the criticism, TRA lays more emphasis on the determinants of deliberate intended behaviour hence the theory being applied extensively in social psychology and other behavioural sciences (Davis, Bagozzi, & Warshaw, 1989). Doswell et al. (2011) adopted TRA to explain sexual behaviour among African American young teenage girls in the United State of

America and found that attitude towards delayed and preventive sexual behaviour was strongly associated with intention than subjective norm. Nguyen et al. (2018) used TRA as the framework for communicating climate risk among school children in Vietnam. The Authors found that attitudes and subjective norms in communication strategies marginally affected the behavioural intentions of school children to seek information on climate change adaptation. Of the two TRA variables, the behavioural intentions for climate change adaptation was affected by only attitude (Nguyen et al., 2018).

Mi, Chang, Lin and Chang (2018) also applied the theory of reasoned action to explain cooperate social responsibility (CSR) behaviour intentions of 2000 Taiwanese cooperations. The study reported that attitude towards CSR and CSR subjective norms significantly predicted behavioural intention towards CSR. The results of Mi et al.'s (2018) is consistent with the findings of (Doswell et al., 2011) and (Nguyen et al., 2018). Similar findings were also reported by Arevalo and Brown (2019) who adopted the reasoned action theory to identify factors influencing organized exercise among Hispanics.

The Theory of Reasoned Action was adopted in the context of this study to show that a behaviour exhibited by farmers is predicted by their intention which can equally be explained by the farmers' attitude and the subjective norm that is associated with the behaviour. Behavioural intention to adopt drone technology services for FAW control, attitude towards the use of the drone and subjective norms of using the drone were used as part of the key variables of the extended technology acceptance model adopted for the study. Attitude in this study is explained as the farmer's evaluation of the drone as a new technology, and defines "belief" as a link between the drone and its attributes,

and defined “behaviour” as an outcome or intention (Fishbein & Ajzen, 1975). The second determinant is the farmer’s subjective norms of the perceived immediate society’s attitude towards the behaviour of using the drone for FAW control. Behavioural intention on the other hand is a measure of the farmer’s intention to use the drone to perform the task of spraying chemical to control the FAW (Fishbein & Ajzen, 1975).

Downs and Hausenblas (2005) posited that, “the key assumptions of the Theory of Reasoned Action is that, farmers will engage in a behaviour once the intention is high, intention increases when a behaviour is favourably assessed (attitude), and influential people in their community related to them urge them (subjective norm) to partake in the behaviour ” (p. 77). The hypothetical propositions put forward by TRA indicate that, attitude and subjective norm predict intention while intention predicts behaviour (Fishbein & Ajzen, 1975). These hypothetical projection of TRA that attitude and subjective norm predicts intention while intention predicts behaviour are the focus of this study.

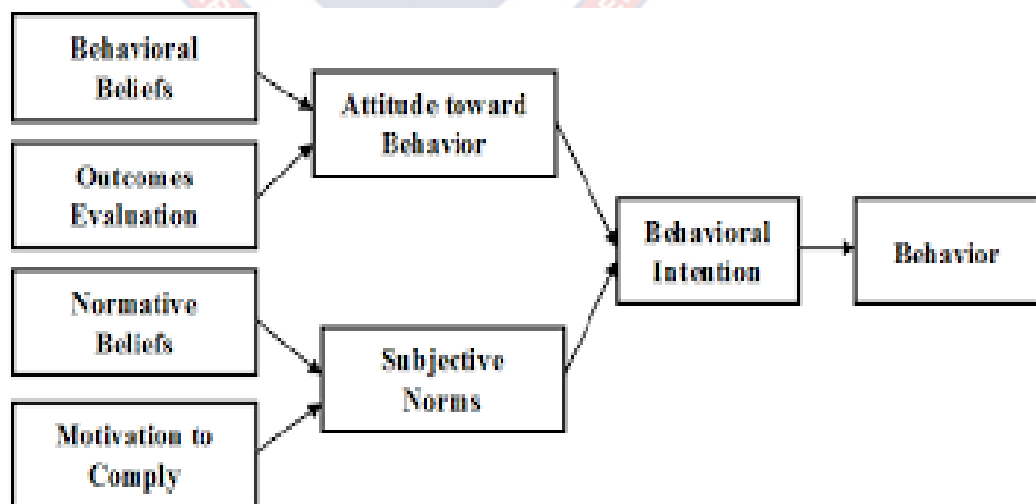


Figure 2: Theory of Reasoned Action (TRA)

Source: Fishbein and Ajzen (1975)

Additionally, a farmer's attitude towards adoption of drone services for spraying pesticides for the control of FAW is indicated by the development of a behavioural intention to adopt the technology. This study sought to examine the influence of attitude and subjective norms on the behavioural intention of maize farmers to adopt the drone technology services for spraying pesticides for the control of FAW (Agarwal, 2000).

The Theory of Planned Behaviour (TPB)

The Theory of Planned Behaviour (TPB) was developed by Icek Ajzen in 1985 (Ajzen, 1991), with the additional construct of Perceived Behavioural Control to the framework of TRA to improve its predictive power (Ajzen & Fishbein, 1988). TPB was used in this study because it is a theory that relates beliefs to behaviour. The theory reveals that, three primary variables, namely: attitude, perceived behavioural control, and subjective norm, collectively predict the behavioural intentions of a person (Ajzen, 1991). Hence, the most proximal determinant of human social activity is believed to be behavioural intention. According to Ajzen (1991), the theory does not only predict behavioural intention but it similarly clarifies it through the precursors of attitude, perceived behavioural control, and subjective norm.

According to Ryan and Carr (2010), the principles of the theory of planned behaviour are based on the notion that individuals make reasonable, reasoned decision to engage in certain behaviour by examining the information offered to them. The Authors further noted that, the performance of a behaviour is dictated by the desire of the person to participate in it (affected by the value placed on the individual's behaviour, the ease with which it may be carried out, and the perceptions of significant others) and the conviction that the behaviour

is under his/her control. The TPB model has been effective in predicting and explaining behaviour based on attitudes, social support, self-efficacy and purpose.

The theory is placed within a more general framework of the relationships between beliefs, attitudes, intentions, and behaviour (Ajzen & Madden, 1986). The three variables predict the individual's intent to perform or adopt a behaviour (van den Heever, 2016). The importance of the three variables is based on individual differences. The attitude of an individual towards a behaviour is indicated by their open views on behaviour (Fishbein & Ajzen, 1975). Amjad and Wood (2009) stated that subjective norm is a person's opinion regarding a given behaviour that is influenced by the opinions of others, (for example; spouse, parents, friends, teachers etc.). Perceived behavioural control is an individual's perceived ease or complexity of executing the particular behaviour (Ajzen, 1991; Ajzen & Fishbein, 1988). Intention is an indication of the desire, readiness, or propensity of an individual to exhibit a given action (Ajzen, 2002). Intention is believed to be an immediate precursor of behaviour.

Intention is based on attitude, perceived behavioural control and, subjective norm, such that the variables are measured for its relevance in reference to the activities and population of interest (Ajzen, 1991). According to Ajzen and Fishbein (1988) behaviour is the quantifiable reaction of somebody with respect to an agreed target in a given situation. Ajzen (1991) indicated that the impact of intention on behaviour is thought to be moderated by perceived behavioural control, so that when perceived behavioural control is high, a favourable intention produces the behaviour. In other words perceived

behavioural control along side intention can be used to directly predict behaviour (Chen, Rong, Ma, Qu, & Xiong, 2017).

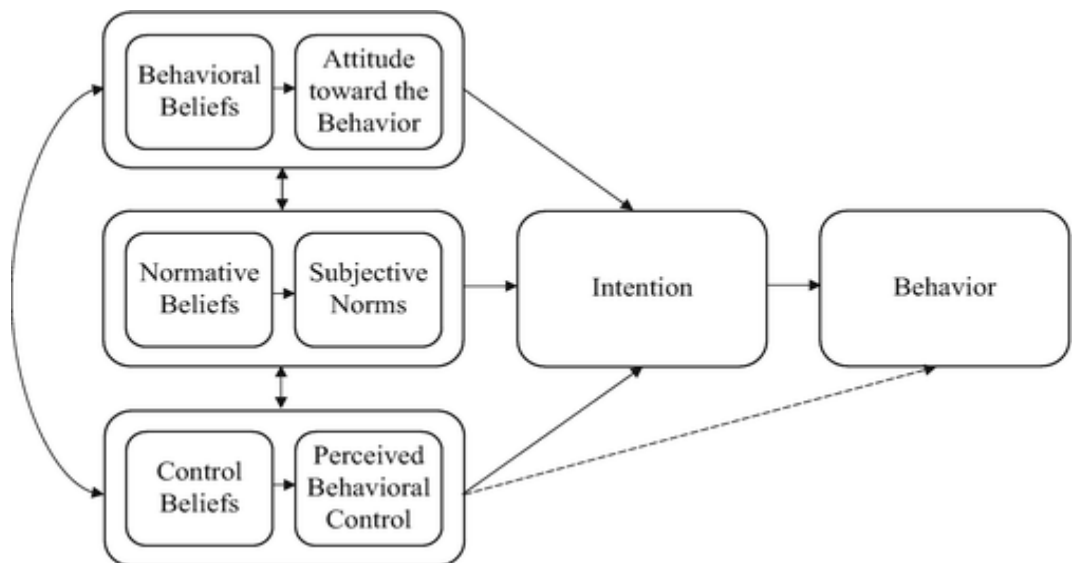


Figure 3: Theory of planned behaviour

Source: Ajzen (1991)

The Theory of Planned Behaviour, like any theory for predicting human behaviour, has its inherent limitations. For example, McEachan, Conner, Taylor and Lawton (2011) posited that TPB's explanatory nature is static, which makes it difficult to explain the evidence of behaviour and future behavioural cognitions. The theory has been critiqued for focusing solely on logical reasoning and ignoring implicit behaviour aspects. (Sheeran et al., 2013). Additionally, Conner, Godin, Sheeran and Germain (2013) also criticised the role of emotions beyond expected affective results in the theory. Other have questioned whether the model's hypotheses are susceptible to empirical falsification or are fundamentally common-sense assertions that cannot be falsified (Ogden, 2003).

Sniehotta, Pesseau and Araújo-Soares (2014) opined that the concern of TPB is about its validity and utility. Validity because, there is evidence that

when TPB predictors are regulated, age, socio-economic status and environmental characteristics predict objectively-evaluated behaviour (Sniehotta et al., 2013). In the primary position of a theory, Sniehotta et al. (2014) indicated that TPB fails in its utility because it does not adequately convey stored empirical evidence. The limitations of TPB can be summarized as follows: it assumes that, regardless of the purpose, the individual acquires the opportunities and resources to succeed in performing the desired behaviour; other factors that affect behavioural intention and motivation, such as anxiety, risk, mood, or past experience, are not accounted for; although normative influences are taken into account, environmental or economic factors that affect the intention of an individual to conduct a behaviour are not taken into account, it assumes that behaviour is the result of a linear process of decision-making, and does not recognize that it can alter over time; again with that important addition of the construct of perceived behavioural control, the theory says little about real control over actions, the theory does not discuss the time period between “intent” and “behavioural action” (LaMorte, 2019b).

In spite of the criticisms, TBP has been applied to predict or explain human behaviour about the adoption of technologies (Bagheri et al., 2019; Karapandzin et al., 2019; Moon et al., 2019). Moon et al. (2019) studied the determinants of green vegetables purchase intention of consumers and found that attitude and subjective norm significantly influenced the intention of customers to purchase green vegetables in Pakistan. Bagheri et al. (2019) reported of significant positive relationship between farmers’ intention to use pesticides and other latent constructs in the TPB model, i.e. subjective norms, perceived behavioural control and attitude. Maleksaeidi and Keshavarz (2019)

also found a strong positive relationship between intention and attitude and subjective norms. This present study adopted the Theory of Planned Behaviour (TPB) to examine the effects of attitude and subjective norms on the behavioural intention of maize farmers to utilize drone spraying services to apply insecticides for FAW control. The variables in TPB were used as part of the framework of the variables in the extended technology acceptance model.

Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) was formulated by Fred D. Davis in 1989 with the aim of developing a framework for computing and describing the adoption and utilization innovations in a social structure is the central theory of the study (Davis et al., 1989; Venkatesh & Davis, 2000). The study by Davis (1989) centred on two theoretical variables, namely: ‘perceived usefulness’ and ‘perceived ease of use’, which are considered to be the fundamental predictors of technology usage. TAM was used in this study to predict the acceptance of drone technology services for control of FAW among maize farmers in Northern Ghana.

The model establishes that a person’s intention to accept and use a new technology is impinged on the perceived usefulness and perceived ease of use (Davis, 1989) which inform the attitude and behavioural intention towards use of the technology (Charness & Boot, 2015; Davis, 1989; Taherdoost, 2018). The underlying principle is that TAM has four core variables: ‘perceived usefulness (PU)’, ‘perceived ease of use (PEOU)’, ‘attitudes toward use of technology (ATT)’, and ‘behavioural intention to use (BI)’. Davis (1989) defined perceived usefulness as “the degree to which a person believes that using a particular technology would enhance his or her job performance” (p. 320). Surendran

(2012) described perceived usefulness as the potential subjective possibility that using the technology would enhance job performance. Perceived ease of use is “the degree to which a person believes that using the technology would be free of effort” (Davis, 1989, p. 320). Davis et al. (1989) described “ease” as “freedom from great effort or difficulty”. Venkatesh and Davis (2000) added that the less effortful a technology, the more using it would improve the performance of the user.

The framework of the second part of TAM was a model based on the Theory of Reasoned Action (TRA) and the Theory of Planned Behaviour (TPB) with the exclusion of subjective norm and perceived behavioural control, respectively (Chen & Chen, 2011; Davis, 1989; Surendran, 2012; Taherdoost, 2018; Xia, Zhang, & Zhang, 2017). Davis (1989) examined a person’s attitude towards a technology and the belief of the users that affect the intention to accept or reject the technology. TAM suggested that technology use is predicted by behavioural intention, except that behavioural intention is jointly determined by its perceived usefulness and the person’s attitude toward the utilization of the technology (Davis et al., 1989). Taherdoost (2018) argued that behavioural intention in TAM is because the two principal beliefs, perceived usefulness and ease of use have substantial influence on attitude of the user towards the use of the technology. The author added that these variables can be denoted as favourableness and unfavourableness toward the adoption of the technology.

Xia, Zhang and Zhang (2017) posited that TAM demonstrates a linkage between external variables and technology usage. The authors described external variables as organisational characteristics, system features and individual differences. Taherdoost (2018) stated the external variables in the

TAM as the characteristics of the system, user training, participation in design and the implementation process. These external variables such as system design features and previous adoption behaviour have direct impact on perceived ease of use and perceived usefulness of technology systems (Chen & Chen, 2011; Farahat, 2012; Scherer, Siddiq, & Tondeur, 2018; Xia et al., 2017).

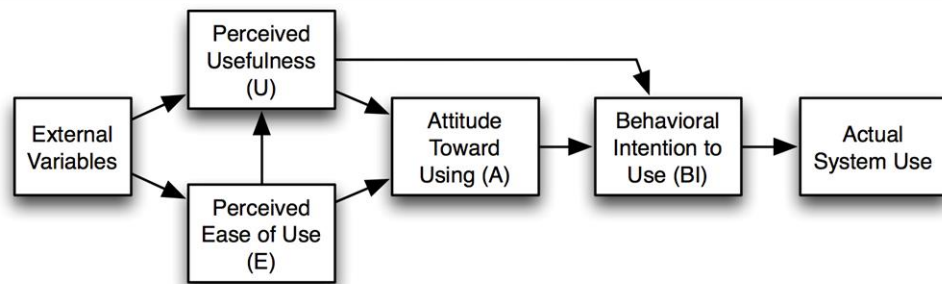


Figure 4: Technology acceptance model

Source: Davis (1989)

Application of TAM has been criticized by many scholars in the field of technology adoption (Charness & Boot, 2015). According to Taherdoost (2018), TAM cannot be applied beyond the workplace because the model ignored the social influence on adoption of technology. Yousafzai, Foxall and Pallister (2007) and Taherdoost and Masrom (2009) argued that the external variables in TAM need to be expanded to include a more reliable prediction of technology system usage. Taherdoost (2018) suggested that intrinsic motivation is ignored in TAM, hence the ability of the model to apply to customer-related frameworks where the acceptance and use of ICTs are not only to accomplish tasks but to satisfy the emotional needs of users, is a limitation.

Venkatesh (2000) posited that the economical nature and predictive authority of TAM though its strongest point is also its fundamental limitation. The author added that the generality of the model does not offer sufficient

understanding from the perspective of providing system designers with the necessary information to create new systems with user acceptance in mind. Nistor (2019) stressed that even though perceived ease of use has comprehensively been used in user acceptance studies, limited understanding on the predictors of PEOU persist with some scholars. Several studies have been conducted that modified the original model proposed by Davis (1989).

Taylor and Todd (1995) postulated a model known as the combined TAM-TPB model which joined the theories of planned behaviour and technology acceptance model. Szajna (1996) also proposed an addition of self-reported system use to TAM. Agarwal and Prasad (1998) modified TAM by including a construct known system compatibility to the model. Venkatesh (2000) recommended integrating control, intrinsic motivation and user emotions into TAM. Venkatesh and Davis (2000) proposed another version of TAM known as TAM 2 which included new variables to the original model. Venkatesh, Morris, Davis and Davis (2003) also formulated the Unified Theory of Acceptance and Use of Technology (UTAUT) Model. Wu and Wang (2005) proposed a modified TAM with variables like perceived risk in the use of the technology, cost of using the technology and compatibility with existing method being used by the user. Venkatesh and Bala (2008) extended TAM 2 into the new version TAM 3. Chen et al. (2017) studied mobile social gaming service and proposed the addition of altruism, social interaction, flow and perceived enjoyment variables. These studies were conducted with the view of overcoming the limitations of TAM.

Another weakness of TAM was the fact that the model explained about 40 percent of the variance in a person's desire or tendency to use a novel

technological systems (Lai, 2017; Venkatesh, 2000). To deal with the marginal variance in the intention of an individual to use a technology, Venkatesh and Davis (2000) proposed two hypothetical courses of action namely: 'cognitive instrumental processes', and 'social influence' to give details about the determinants on perceived usefulness (PU) and behavioural intention (BI) known as the extended technology acceptance model TAM 2. Subjective norms and images were components of social influence (Alomary & Woollard, 2015), while job relevance, output quality, result demonstrability and perceived ease of use were the components of cognitive instrumental processes (Venkatesh & Davis, 2000).

The variable perceived ease of use from the novel TAM as a direct determinant of perceived usefulness is kept by TAM 2. All the added variables are understood to influence the acceptance of new technologies (Alomary & Woollard, 2015). TAM2 had two moderating variables which are experience and voluntariness (Venkatesh & Davis, 2000). The extended model (TAM2) omitted attitude from the framework (Alomary & Woollard, 2015; Jaradat & Al-Mashaqba, 2014). In TAM, Davis had argued that the effect of subjective norms (as posited in the theory of reasoned action) on behavioural intention of individuals to use technologies could be ignored, hence was not considered in TAM. However, Venkatesh and Davis (2000) re-examined these variables in TAM2 and posited that, subjective norms and image have a positive effect on perceived usefulness through processes of internalisation and identification respectively. The TAM2 additionally posited that the influence of subjective norm on both perceived usefulness and behavioural intention will alternate as

the users of technologies acquire experience with the technology (Venkatesh & Davis, 2000).

Venkatesh and Bala (2008) in a bid to make TAM more comprehensive, combined models suggested by Venkatesh (2000) and Venkatesh and Davis (2000) to develop a complete nomological network of digital technology adoption and use referred to as TAM 3. The model proposed additional constructs as determinants of the TAM construct perceived usefulness (PU), perceived ease of use (PEOU) and behavioural intention (BI). The TAM 3 combined the variables of TAM 2 with new determinants PEOU, i.e. self-efficacy, perceptions of external control, anxiety, playfulness, perceived enjoyment and objective usability (Jaradat & Al-Mashaqba, 2014; Venkatesh & Bala, 2008). The theoretical underpinning of TAM 3 represented an aggregate body of knowledge developed over decades of TAM research results in four different determinants of perceived ease of use and perceived usefulness known as individual variances, system features, social effect and enabling conditions (Venkatesh & Bala, 2008).

Individual difference variables are personality and demographics variables that can influence a person's perception of ease of use, and usefulness. Also, system attributes are unseen elements of a system that might influence people's views of a technology's utility or ease of use. Social influence refers to the social processes and procedures that lead people to form opinions on various aspects of technology. Finally, organizational support that aids in the usage of technology was represented by enabling conditions.

TAM 3 has been applied in different studies to predict and explain varying agricultural information technologies and hypothetical correlations of

the adoption behaviour of agricultural actors (Flett et al., 2004; Jokar et al., 2017; Kim & Woo, 2016; Sharifzadeh et al., 2017; Tohidyan Far & Rezaei-Moghaddam, 2015; Verma & Sinha, 2018). This study used the extended technology acceptance model (TAM 3) to examine acceptance of drone technology services for control of FAW among maize farmers in Northern Ghana (Venkatesh & Bala, 2008). The model was used to predict the intention of the farmers to adopt drone technology services for control of the destructive pest and how the characteristics of the technology, that is, its perceived ease of use and usefulness positively influenced farmers' attitude towards using the technology.

Chen and Chen (2011) posited that the effects of both perceived usefulness and perceived ease of use on attitude towards the ICTs are presumed to be positive in TAM. Therefore, this study hypothesized that when a maize farmer's perceptions of the ease of use and usefulness of drone technology services increase, the farmer is likely to develop positive attitude towards adopting the services of the technology for spraying pesticides for control of FAW. Chen and Chen (2011) again argued that, perceived ease of use is presumed to have direct, positive influence on perceived usefulness whilst both attitude towards use and its perceived usefulness have direct, positive influence on the behavioural intention. This study also measured the effect of perceived ease of use on usefulness, and how usefulness and attitude influenced the behavioural intention of the maize farmers to adopt drone spraying services for control of Fall Armyworm in Northern Ghana. The study also assessed the predictors of both perceived usefulness and ease of use.

Determinants of Perceived Usefulness (PU)

‘Perceived usefulness’ as utilized in this study is the extent to which a maize farmer considers that drone technology services for pesticides application for the control of FAW will enhance productivity or performance (Davis, 1989; Venkatesh & Bala, 2008; Venkatesh & Davis, 2000). Perceived usefulness acted as a motivational influence for a maize farmer to develop the attitude towards the adoption of drone technology services for pesticides application for the control of FAW in the study area (Amin et al., 2015). From the perspective of agriculture and pest management, it is the perceived likelihood that the drone technology services for pesticides application for the control of FAW will unequivocally benefit the maize farmer. Amin et al. (2015) and Lai (2017) noted that perceived usefulness is a strong determinant of technology acceptance, adoption, and usage behaviour. According to Venkatesh and Davis (2000), perceived usefulness is influenced by seven constructs ranging social influence processes (‘image’, ‘subjective norm’ and ‘voluntariness’) and cognitive instrumental processes or system characteristics (‘results demonstrability’, ‘output quality’, ‘job relevance’ and ‘perceived ease of use’).

The operationalisation of the predictors of PU of technology included the moderating effect of experience and voluntariness (Venkatesh & Davis, 2000). In predicting and explaining perceived usefulness, Venkatesh and Bala (2008) found out that, subjective norm, and result demonstrability, and image were major determinants of PU. Job relevance and output quality on the other hand have an interactive influence on PU in a way that increasing output quality, results in stronger influence of job relevance on PU.

Venkatesh and Bala (2008) also revealed the moderating effect of experience on subjective norms and PU, however, the impact is weaker with increasing experience. The impact of subjective norms on image was significant. The author again noted that, the impact of perceived ease of use on PU was moderated by experience, while the determinants of PEOU did not have any significant influence on PU over and above the other determinants of PU. Experience moderated the relationship between PEOU, and PU in a manner that with increasing experience, the impact became stronger (Venkatesh & Davis, 2000). Venkatesh and Bala (2008) posited that the drivers (PEOU, output quality, subjective norm, job relevance, image, and demonstrability) jointly explained 52 to 67 percent of the variations seen in perceived usefulness.

Similar findings were conveyed by Al-gahtani (2016) who found significant relationships between perceived usefulness and subjective norms ($\beta = 0.349, p < 0.001$) and image ($\beta = 0.133, p < 0.001$). The author also found a significant relationship between image and subjective norms ($\beta = 0.435, p < 0.001$) with moderating effect of experience.

Table 1: Determinants of perceived usefulness

Determinants	Definitions
Perceived ease of use	The extent to which a farmer believe that deploying drone technology will be painless (Davis, Bagozzi, & Warshaw, 1989).
Subjective norm	The extent to which a farmers believes that majority of individuals who matter to him or her believe he or she should or should not utilize the drone (Davis et al., 1989; Fishbein & Ajzen, 1975).

Image	The extent to which a farmer believe that using the drone will elevate his or her social standing in the community (Moore & Benbasat, 1991).
Job Relevance	The extenst to which a farmer believes the drone can be used to control FAW (Venkatesh & Davis, 2000).
Output Quality	The extent to which a farmer believes tha drone is effective when used for FAW control (Venkatesh & Davis, 2000).
Result Demonstrability	The extent to which a farmer believes that the benefits of employing the drone to control Fall Armyworms are tangible, observable, and communicated (Moore & Benbasat, 1991).

Source: Venkatesh and Bala (2008)

The four latent construts (perceived ease of use, job relevance, output quality and result demonstrability), represent the effect of cognitive instrumental processes on perceived usefulness (Venkatesh & Davis, 2000). Al-gahtani (2016) reported that, only two cognitive instrumental processes [job relevance ($\beta = 0.380$, $p < 0.001$) and perceived ease of use ($\beta = 0.206$, $p < 0.001$)] had significant effect on perceived usefulness, with output quality also significantly moderating the relationship between job relevance and perceived usefulness.

The author further reported that, result demonstrability was the only latent variable which did not statistically influence perceived usefulness, indicating that the respondents of the study did not believe the results of using the online learning management system were tangible, observable and communicable (Moore & Benbasat, 1991). Perceived ease of use, job relevance, image, subjective norm, and output quality compositely explained 42.4 percent of the variation in perceived usefulness ($R^2 = 0.424$) of adopting online learning management systems among Saudi Arabian college students (Al-gahtani, 2016).

The moderating effect of experience is also reported by in literature. Al-gahtani (2016) found out that experience with a technology negatively moderated the effect of subjective norm on perceived usefulness ($EXP \times SN \rightarrow PU = -0.05$). On the contrary, the impact of PEOU on PU was positively regulated by experience ($EXP \times PEOU \rightarrow PU = 0.083$) while output quality also significantly moderated the impact of job relevance on usefulness ($OQ \times REL \rightarrow PU = 0.152$).

Fosso Wamba and Trinchera (2014) also found a strong relationship between perceived ease of use and perceived usefulness (standardized β between 0.561 and 0.813, $p = 0.000$). With respect to the coefficient of determination (R^2), perceived ease of use independently explained between 33 percent and 66 percent of the variation in the perceived usefulness of the adoption social media in agriculture (Fosso Wamba & Trinchera, 2014). Riskinanto, Kelana, and Hilmawan (2017) reported that, there was a very strong positive relationship between perceived ease of use and perceived usefulness ($\beta = 0.853$, $p < 0.01$), with the perceived ease of use accounting for 72.76 percent of the variation in usefulness ($R^2 = 0.728$). Sevlm, Yüncü, and Hall (2017) again found perceived ease of use to positive and significant influence on perceived usefulness ($\beta = 0.259$, $p < 0.01$).

Shukla and Sharma (2018) studied the application of technology acceptance model for evaluating consumers' adoption of mobile technology for grocery shopping. The authors found a very strong relationship between PEOU and PU ($\beta = 0.631$, $p = 0.000$). The result implied that if the clients of grocery shops perceive the usage of mobile devices for procuring provisions as easy, it was possible they would find it useful as well. Shukla and Sharma (2018) also

reported that, perceived ease of use explained approximately 40 percent ($R^2 = 0.398$) of the variance in perceived usefulness. Gbongli, Xu, and Amedjonekou (2019) also reported of positive significant relationship between perceived ease of use and usefulness ($\beta = 0.357, p < 0.01$). Perceived ease of use explained less than 22.3 percent of the variations in perceived usefulness ($R^2 = 0.223$). This study examined the effect of the social influence processes and cognitive instrumental process on perceived usefulness.

Determinants of Perceived Ease of Use (PEOU)

Perceived ease of use is defined as the extent to which a person believes that using a technology is simple and easy (Davis, 1989; Venkatesh & Bala, 2008; Venkatesh & Davis, 2000). Amin et al. (2015) indicated that many scholars have extensively studied the variable perceived ease of use in order to gain understanding of user acceptance and adoption of new innovations leading to the operational determinants of perceived ease of use of technologies. Venkatesh (2000) studied employees of three organisations and proposed a model of the determinants of technology specific perceived ease of use based on anchoring and adjustment-based theory. The author found that internal and external control (conceptualized as computer self-efficacy and facilitating conditions respectively), intrinsic motivation (conceptualized as computer playfulness), and emotion (conceptualized as computer anxiety) are proposed as anchor variables that influence early beliefs of a technology's ease of use.

Venkatesh and Bala (2008) integrated the determinants of perceived ease of use (Venkatesh, 2000) and TAM 2 (Venkatesh & Davis, 2000) and developed TAM 3 with both models. Venkatesh and Bala (2008) found that, computer self-efficacy, perception of external control, computer anxiety and

computer playfulness significantly influenced perceived ease of use. The result as posited by Venkatesh and Bala (2008) is consistent with Venkatesh (2000) who also found same. Venkatesh and Bala (2008) also found out that the adjustments, perceived enjoyment and objective usability showed inconsistent effect on perceived ease of use. The application of drone technology services for Fall Armyworm control was investigated in this study. Variable objective usability was eliminated from the study because the participants of the study who were farmers who would be using the services of drone services providers. The farmers did not have the competence to use the drone to perform the spraying task for the control of FAW since they were not licensed. Therefore the effect of objective usability on PEOU was not tested.

Table 2: Determinants of perceived ease of use

Determinants	Definitions
Computer Self-Efficacy	The extent to which a farmer believes the drone spraying services operator is capable of doing the spraying task with the drone (Compeau & Higgins, 1995a, 1995b).
Perception of External Control	The extent to which a farmer believes that organizational and technical resources are available to support the employment of drone spraying services for pesticides application in the control of FAW (Venkatesh et al., 2003).
Computer Anxiety	The extent to which a farmer is concerned about the possibility of adopting drone spraying for Fall Armyworm control (Venkatesh, 2000, p. 349).
Computer Playfulness	The cognitive spontaneity of a farmer when it comes to the employment of a spraying drone for FAW control (Webster & Martocchio, 1992, p. 204).

Perceived Enjoyment	The extent to which deploying the drone to spray pesticides for control of FAW is regarded as a fun pastime in and of itself (Venkatesh, 2000, p. 351).
Objective Usability	“The drone comparison based on the real level (rather than perceived) of effort necessary to execute the spraying task” (Venkatesh, 2000, pp. 350-351).

Source: Venkatesh and Bala (2008)

Venkatesh and Bala (2008) also posited that theoretically, experience moderated the influence of computer anxiety on PEOU, in a way that impact became stronger when experience decreases. The authors also reported that the determinants of perceived usefulness had no significant effect on perceived ease of use. However, computer anxiety, computer playfulness, computer self-efficacy, perception of external control, and perceived enjoyment accounted for about 43 and 52 percent of the variations in PEOU. Al-gahtani (2016) studied the usage of online learning management systems among Arabian college students and found that four anchor latent constructs had significant influence on PEOU with the perception of external control having the strongest impact (perceived enjoyment - $\beta = 0.201$, $p < 0.001$; self-efficacy - $\beta = 0.176$, $p < 0.001$; computer anxiety - $\beta = -0.105$, $p < 0.001$; perceived external control $\beta = 0.454$, $p < 0.001$).

Al-gahtani (2016) however, recorded no significant impact of computer playfulness on PEOU which indicated the absence of intrinsic motivation among Arabian college students using online learning management systems. The strongest impact on PEOU exhibited by perceived external control among anchors variables showed how the college students' control perceptions about the organization's resources and support structures make it easier to use the learning management systems (Al-gahtani, 2016). This result supported the key

role of PEC to PEOU as reported by (Venkatesh, 2000). Al-gahtani (2016) also reported that the anchor variables collectively accounted for 45 percent of the variations in perceived ease of use ($R^2 = 0.450$) with experience negatively moderated the impact of anxiety on PEOU ($EXP \times CANX \rightarrow PEOU = -0.035$) while the effect of playfulness on ease is positively moderated by experience ($EXP \times ENJ \rightarrow PEOU = 0.076, p < 0.05$).

SevİM et al. (2017) analysed the online travel products with the extended technology acceptance model which found that perceived enjoyment positively and significantly influenced perceived ease of use ($\beta = 0.557, p < 0.01$). The authors also reported that, perceived enjoyment explained 31% of the variation in perceived ease of use ($R^2 = 0.310$). Gbongli et al. (2019) reported of positive relationships between perceived ease of use and anxiety and self efficacy respectively ($\beta = 0.119, p < 0.05; \beta = 0.193, p < 0.01$). However, the effect of the two latent constructs was low (5.8%) in explaining the variance in perceived ease of use ($R^2 = 0.058$). Note worthy is the fact that the remaining 94.2 percent, can be elucidated by other variables not included in their model such as perceived external control, playfulness and enjoyment.

Determinants of Attitude towards use and Behavioural intention to use

As postulated by the TAM constructs, an individual's attitude towards using and intention to use any technology is greatly influenced by latent variables such as perceived usefulness (PU) and perceived ease of use (PEOU) (Davis, 1989). Within the framework of this study, attitude is defined as the evaluative judgment of a maize farmer in adopting drone technology for the application of pesticides for the control of FAW (Davis, 1989; Venkatesh & Davis, 2000). Attitude toward adoption has been established by many scholars

to play significant role in technology acceptance (Amin et al., 2015; Shukla & Sharma, 2018).

For instance, Amin et al. (2015) reported of positive significant relationships between attitude and PU ($\beta = 0.373, p = 0.00$) and PEOU ($\beta = 0.270, p = 0.00$), the two constructs explain approximately 32 percent of the variations in the attitude of mobile wallet consumers in Bangladesh ($R^2 = 0.318$). Riskinanto et al. (2017) also found positive relationships between attitude and perceived ease of use ($\beta = 0.298, p < 0.01$) and perceived usefulness ($\beta = 0.636, p < 0.01$) with both variables accounting for 81.81 percent of the variance in attitude towards use ($R^2 = 0.8181$). Similar findings were reported by SevİM et al. (2017) which revealed positive, significant influence of perceived ease of use on attitudes toward online shopping products ($\beta = 0.523, p < 0.01$).

Shukla and Sharma (2018) studied the adoption of mobile technology for grocery shopping in India and found a strong relationship between attitude and PU ($\beta = 0.562, p = 0.00$) and PEOU ($\beta = 0.323, p = 0.00$), indicating that when a customer of a grocery shop found the use of mobile technology for shopping as useful and easy to use, they developed a favourable attitude towards the use of the technology. The authors also revealed that the two latent constructs compositely explained approximately 65 percent of the variations in the attitude towards use ($R^2 = 0.649$). Similar findings were reported by Gbongli et al. (2019) who found positive relationship between attitude and PU ($\beta = 0.408, p < 0.01$) and PEOU ($\beta = 0.357, p < 0.01$). The authors also reported that PU and PEOU were the best predictors of attitude in their study, as the variables accounted for 50 percent of the variations in attitude ($R^2 = 0.502$).

Behavioural intention in this study is the intention or willingness of the maize farmers to utilize drone spraying for application of pesticides for control of FAW in the study area. Venkatesh and Bala (2008) found out that PU was the strongest predictors of the desire, intention, but, PEOU ensured an inconsistent impact on behaviour. The authors is however, reported that, experience moderated on the relationship between PEOU and behavioural intention. The authors also recorded experience actually had a moderating influence on perceived ease of use (PEOU x EXP) on behavioural intention in a manner that the impact is low with higher experience.

The effect of years of farming experience of the maize farmers was used in analysis of this study. The years of farming experience was estimated on the ratio measurement scale to measure the number of years each farmer has been cultivating maize in the study area. Years of farming experience was used to test its effect on the relationships in the model because, Bagheri et al. (2019) and Karapandzin et al. (2019) proposed that socio-demographic characteristics such as experience be used a moderating variable to test its impact on the behavioural intention of farmers towards safe use of pesticides. Venkatesh and Bala (2008) revealed that there is a two-way interaction between subjective norm and voluntariness (SN x VOL) indicating that the impact of subjective norm on behavioural intention was stronger in a mandatory context. The authors also found a two-way interaction between subjective norm and experience (SN x EXP) on behavioural intention as a result of which the subjective norm's influence diminishes as experience grows. TAM 3 predicted between 40 to 53 percent variance in behavioural intention.

Al-gahtani (2016) studied the use of online learning management systems by college students in Saudi Arabia reported that three latent variables [PEOU ($\beta = 0.206, p < 0.001$); subjective norms ($\beta = 0.349, p < 0.001$); PU ($\beta = 0.374, p < 0.001$)] significantly accounted for 42 percent of the variance in behavioural intention ($R^2 = 0.420$). Al-gahtani also reported that experience negatively moderated the effect of subjective norm on behavioural intention ($\text{EXP} \times \text{SN} \rightarrow \text{BI} = -0.10$). The negative coefficient implies that, more experienced college students are less likely to be affected by opinions than others in relationship to their intention to use LMS. On the contrary, Al-gahtani (2016) reported that PEOU's influence on behavioural intention was moderated by experience ($\text{EXP} \times \text{PEOU} \rightarrow \text{BI} = 0.101$). The positive coefficient indicates that impact of PEOU on the intention to use LMS among the college students did not reduce with increasing experience.

Empirical review of the literature on the significant predictors of behavioural intention also showed a strong relationship between intention, and PU and attitude towards use (Amin et al., 2015; SevİM et al., 2017; Shukla & Sharma, 2018). Amin et al. (2015) reported that, there is a significant relationship between attitude ($\beta = 0.487, p = 0.00$) and usefulness ($\beta = 0.302, p = 0.00$) and behavioural intention. The relationship between behavioural intention and perceived ease of use was however, negative and non-significant ($\beta = -0.110, p > 0.05$). The study revealed that the three independent variables collectively predicted 40 percent of the variance in behavioural intention. Similar finding was reported by SevİM et al. (2017) when they revealed that in their study, perceived usefulness and attitudes toward online shopping had a

positive and significant relationship with behavioural intention ($\beta = 0.410, p < 0.01$; $\beta = 0.384, p < 0.01$)

Shukla and Sharma (2018) reported a significant relationship between and PU ($\beta = 0.435, p = 0.000$) and attitude towards use ($\beta = 0.317, p = 0.000$) and behavioural intention, with the two latent variables explaining 50 percent of the variation of the behavioural intention of customers of the grocery shop to adopt mobile technology for shopping. The results imply that, when the customers of the grocery shop found the use of mobile technology for shopping to be useful and develop a positive attitude towards the use of the technology, they would have the intention to use the technology. Further review of the results of Shukla and Sharma (2018) showed that, perceived usefulness had a partial mediating relationship between perceived ease of use and intention while attitude towards use also had a mediating relationship between usefulness and intention to use mobile technology for grocery shopping. Gbongli et al. (2019) reported a positive significant correlation between behavioural intention and attitude towards use ($\beta = 0.255, p < 0.01$), with attitude explaining less than 14.6 percent of the variance in behavioural intention ($R^2 < 0.146$).

Hypotheses for TAM 3 Structural Model

H₀ (6a): Perceived usefulness (PU) of drone technology services for the control of FAW will have a positive effect on behaviour intention.

H₀ (6b): Attitude toward usage (ATT) of drone technology services for the control of FAW will have a positive effect on behaviour intention (BI).

H₀ (6c): Perceived ease of use (PEOU) of drone technology services for control of FAW will have a positive influence on behaviour intention (BI).

H₀ (6d): The social effect process variable (SN) will have significant impact behavioural intention (BI) to accept drone services for Fall Armyworm control.

H₀ (6e): Perceived usefulness (PU) of drone technology services for the control of FAW will have a positive effect on Attitude toward usage (ATT).

H₀ (6f): Perceived ease of use (PEOU) of drone technology services for control of FAW will have a positive effect on Attitude toward usage (ATT).

H₀ (6g): Attitude towards usage (ATT) will mediate the relationship between perceived ease of use (PEOU) and behavioural intention (BI) to use drone technology services for the control of FAW.

H₀ (6h): Attitude towards usage (ATT) will mediate the association between perceived usefulness (PU) and behavioural intention (BI) to accept drone services for Fall Armyworm control.

H₀ (6i): The impact of SN on behaviour intention (BI) to employ drone technology services for FAW management will be greatly moderated by VOL as social construct.

H₀ (7a): The social effect process variables (SN) will have positive impact on perceived usefulness (PU) of drone technology services for control of FAW.

H₀ (7b): The perceived usefulness (PU) of drone technology services for FAW control will be positively influenced by the social construct Image (IMG).

H₀ (7c): The impact of SN on PU of drone technology services for FAW control will be mediated by IMG as a social construct.

H₀ (7d): The cognitive instrumental process variable (REL) will have positive effect on perceived usefulness (PU) of drone technology services for control of FAW.

H₀ (7e): The cognitive instrumental process variable (RES) will have positive effect on perceived usefulness (PU) of drone technology services for control of FAW.

H₀ (7f): The cognitive instrumental process variable (PEOU) will have positive perceived usefulness (PU) of drone technology services for control of FAW.

H₀ (7g): The influence of REL on perceived usefulness (PU) of drone technology services for FAW control will be moderated by the cognitive instrumental process variable (OQ).

H₀ (7h): Perceived usefulness (PU) will significantly mediate the indirect relationship between cognitive instrumental process variable (PEOU) and BI to accept drone services for Fall Armyworm control.

H₀ (7i): Perceived usefulness (PU) will significantly mediate the indirect relationship between cognitive instrumental process variable (RES) and BI to accept drone services for Fall Armyworm control.

H₀ (7j): Perceived usefulness (PU) will significantly mediate the indirect relationship between social influence process variable (SN) and BI to accept drone services for Fall Armyworm control.

H₀ (7j): Perceived usefulness (PU) will significantly mediate the indirect relationship between social influence process variable (IMG) and BI to accept drone services for Fall Armyworm control.

H₀ (8a): The anchor variable (CSE) will have positive effect on perceived ease of use (PEOU) of drone technology services for control of FAW.

H₀ (8b): The anchor variable (PEC) will have positive effect on perceived ease of use (PEOU) of drone technology services for control of FAW.

H₀ (8c): The anchor variable (CANX) will have positive effect on perceived ease of use (PEOU) of drone technology services for control of FAW.

H₀ (8d): The anchor variable (CPLY) will have positive effect on perceived ease of use (PEOU) of drone technology services for control of FAW.

H₀ (8e): The adjustment variable (ENJ) will have positive effect on perceived ease of use (PEOU) of drone technology services for control of FAW.

H₀ (8f): The cognitive construct (PEOU) would positively mediate indirect relationship between anchor variable (ANX) and behavioural intention (BI) to use drone technology services for control of FAW.

H₀ (8g): The cognitive instrumental process variable (PEOU) will significantly mediate the indirect relationship between anchor variable (PLAY) and BI to accept drone services for Fall Army control.

H₀ (8h): The cognitive instrumental process variable (PEOU) will significantly mediate the indirect relationship between anchor variable (PEC) and BI to accept drone services for Fall Armyworm control.

H₀ (8i): The cognitive instrumental process variable (PEOU) will significantly mediate the indirect relationship between adjustment variable (ENJ) and BI to accept drone services for Fall Armyworm control.

H₀ (8j): The cognitive instrumental process construct (PEOU) will not significantly mediate the indirect relationship between anchor variable (ANX)

and perceived usefulness (PU) to use drone technology services for control of FAW.

H₀ (8k): The cognitive instrumental process variable (PEOU) will not significantly mediate the indirect relationship between anchor variable (PLAY) and perceived usefulness (PU) to use drone technology services for control of FAW.

H₀ (8l): The cognitive instrumental process variable (PEOU) will not significantly mediate the indirect relationship between anchor variable (PEC) and perceived usefulness (PU) to use drone technology services for control of FAW.

H₀ (8j): The cognitive instrumental process variable (PEOU) will not significantly mediate the indirect relationship between adjustment variable (ENJ) and perceived usefulness (PU) to use drone technology services for control of FAW.

H₀ (9Years of farming experience (EXP) as a TAM3 moderator will help to monitor the seven intended paths as demonstrated in Figure 2.

Maize Production in Ghana

CGIAR-IEA (2015) posited that maize (*Zea mays* L.) is one of the most valuable crops for poor farmers and consumers in developing countries, supplying at least 30% of calories to nearly 5 billion people in 94 countries. The author added that due to its importance, the market price for maize is predicted to increase by 100 percent in developing countries in the next 35 years. MoFA (2017) argued that in Ghana, maize is a major food crop, accounting for more than half of the country's total grain production. The cereal is one of the country's main staple crops, grown and consumed by the majority of farming

households. Scheiterle and Birner (2018) added that the crop is historically grown under rain-fed conditions by more than half of rural households in all growing regions. Furthermore, 16 percent of urban households participate in its production (Quiñones & Diao, 2011).

Darfour and Rosentrater (2016) posited that maize became regarded as an important crop in Ghana's southern regions after its introduction in the late 16th century as the widely-grown and eaten cereal grain, with production growing steadily since 1965. The authors added that maize has almost replaced conventional staple crops like sorghum and pearl millet in northern Ghana. The agro-ecological conditions in Ghana differ greatly (Quiñones & Diao, 2011). The four principal ecological zones appropriate for maize cultivation in Ghana are the Forest, Transition, Coastal Savannah, and Guinea Savannah Zones (MoFA, 2017).

Darfour and Rosentrater (2016) posited that a thin belt of savannah stretches along the shore, making up the coastal savannah zone and broadens near Ghana's east coast, where maize and cassava are mostly intercropped. The authors went on to say that this region has a bimodal annual rainfall of about 800 mm, with low productivity due to weak soils. Again, Darfour and Rosentrater (2016) indicated that the forest zone, which runs only inland from the coastal savannah, is semi-deciduous, with a narrow fragment of high rain forest near the Ivory Coast's border in the country's south-western corner, where maize is inter-cropped with cassava, plantain, and cocoyam. The annual rainfall is around 1,500 mm, and maize is planted in both the major rainy seasons, which are respectively March and September (MoFA, 2017).

Furthermore, Darfour and Rosentrater (2016) again noted that as one approaches northern Ghana, the forest zone gradually loses place to the transition zone. This zone is significant for commercial grain production because of its deep, friable soils and minimal tree cover, which allows for progressive cultivation. Maize is farmed as a mono-crop during both the major and minor wet seasons, with annual rainfall average roughly 1,300 mm (MoFA, 2017). To end with, Darfour and Rosentrater (2016) stated that the Guinea Savannah zone encompasses the majority of Ghana's northern lands with a single rainy season with an average rainfall of 1,100 mm. Millet and Sorghum are the common grain, however, maize is also produced (MoFA, 2017).

MoFA (2007) posited that maize supply is not keeping up with demand. Wongnaa and Awunyo-Vitor (2019) argued that with a larger proportion of maize supply going to food consumption in Ghana, increasing its yield is unquestionably important for the country's food security. In addition, since maize is a major component of livestock and poultry feed, the poultry and livestock industries' productivity and growth are dependent on maize. Regardless of the commercial significance of the crop, Ragasa, Chapoto and Kolavalli (2014) posited that Ghana's annual maize yield remains among the world's lowest, well below the average for Africa, south of the Sahara and also smaller than yields in Asia and Caribiana in similar lowland, rainfed tropical conditions.

Scheiterle and Birner (2018) noted that the yield gap is wide, particularly in the northern part of Ghana. According to MoFA (2017), the average maize yields range from 1.2 to 1.9 metric tons (Mt) per hectare (ha), while on-station and on-farm trials indicate that yields of 4 to 6 Mt/ha are possible in the region.

Wongnaa and Awunyo-Vitor (2019) added that the yields are less than 35% of the predicted 5 Mt/ha average potential yield. The authors argued that a drop in productivity would mean a drop in overall maize production, posing a danger to food security, and the poultry and animal subsector's growth.

Low yields are generally associated with low input use and slow technology adoption (MoFA, 2017). Scheiterle and Birner (2018) argued that in most African countries, agricultural production falls short of its potential, especially for maize yields. Wongnaa and Awunyo-Vitor (2019) noted that one of the most popular theories for the low yields in Ghana's maize farms is the presence of scale inefficiencies. Adu et al. (2014) indicated that low plant populations, insufficient planting time, inadequate weed control, lack of credit, limited use of inputs (especially fertilizer and improved seeds) as well as untimely application of adequate quantities of fertilizers, and inadequate drying and storage facilities all contribute to high post-harvest losses and poor marketability of maize are some of the challenges of maize production in Ghana. The authors noted that drought during critical early stages of crop development, low soil nutrient levels (particularly nitrogen and phosphorus), striga, and pest and disease infestations are the key constraints to maize production. Kumar, Kaur, Suby, Sekhar and Lakshmi (2018) posited that farmers' yields are much lower than the variety's built-in yield potential due to the impact of these challenges, particularly pest infestation.

There are over 160 insect and mite species that attack maize crops, according to early literature (Bhutani, 1961; Fletcher, 1914, 1917). However, later research by Mathur (1987) found over 250 pest species associated with maize in field and storage conditions. Dicke and Guthrie (1988) also found 87

species that cause extreme stress on corn production in tropical and temperate regions around the world, either directly or indirectly. Sarup, Siddiqui and Marwaha (1987) studied the trends in maize pest management and observed that there are more than 130 insect pests which have been found to cause corn damage, but only about a dozen cause economic losses. Adu et al. (2014) cited stem borers, cutworms, grasshoppers, weevil's termites, and greater grain borer as the major corn pests which cause economic losses in Ghana. Another major maize pest which is wreaking havoc and causing significant yield and economic losses in Africa, and for that matter Ghana, is the Fall Armyworm (Benson, 2017; Sisay et al., 2019).

Origin, Biology and Distribution of Fall Armyworm (FAW)

The Fall Armyworm (*Spodoptera frugiperda* J. E. Smith) is a native pest in South and North America. According to Luginbill (1928), the insect was first named *Phalaena frugiperda* by James Edwards Smith and John Abbot in 1797. The author noted that FAW is one of only a few insects known to science that disperse and breed across a large portion of the United States during the summer season, only to die at the end of the season. He also added that in the warmer parts of the South, fall army worms stay as permanent residents. Abrahams et al. (2017) posited that the FAW is now scientifically known as *Spodoptera frugiperda* (J. E. Smith). The pest is an arthropod in the order *Lepidoptera*, the larvae of the fall armyworm moth (Goergen et al., 2016). According to Mengestu (2017), the FAW has been a pest in Central, Eastern, and Southern America for more than 150 years, and it has been very successful as a pest because it can feed on up to 186 crop species from a wide variety of crop families, with a particular preference for corn. The author added that the insect

reproduces rapidly and can fly long distances at high speeds, with adults flying up to 100 kilometres per day.

The FAO (2020) established that *Spodoptera frugiperda* (J. E. Smith) is a moth (adult stage) with a phytophagous caterpillar (Lepidoptera: Noctuidae) that feeds on a variety of crops, including maize. Abrahams et al. (2017) noted that the FAW remained in the Americas until early 2016, when it was first discovered in West and Central Africa. Some scholars are however unclear how the haplotype that exists in Africa got there, but DNA barcoding evidence suggests that it came from Florida in the United States, and the Caribbean (Day et al., 2017). The FAO (2017) argued that the growth stages of the Latin America FAW is completed in approximately 30 days (when the temperature is 28°C) during the hot summer period, but it can take up to 60–90 days in cooler weather. The author added that the egg, the six caterpillar growth stages (instars), pupa, and moth are all part of the FAW life cycle. The life stages of FAW does not have the potential to diapause if conditions are appropriate, (particularly in several countries south of the Sahara, where there is no winter) and population of the pest are prevalent (a reproductive resting period) (Kruger, 2017). The FAO (2018) noted that when environmental conditions permit, migrating FAWs arrive in non-endemic locations, and they may only have one generation before becoming extinct locally.

According to the FAO (2020), the adult moths are either male or female nocturnals, with different coloration on their forewings. The author noted that the female moth usually deposits the bulk of her eggs during the first 5 days of her life after a preoviposition period of 3 to 4 days, but an oviposition can last up to 3 weeks. Benson (2017) observed that the total of eggs per mass varies,

but is normally between 100 and 200 pieces, with a maximum of over 2,000. Total egg output per female is around 1,500. During the hot summer months, the egg stage lasts only 2 to 3 days (FAO, 2017). The FAO (2018) estimated that a typical FAW has six larval instars. The author noted that the larvae are more likely to hide during the day's brightest hours but the stage lasts 14–30 days, contingent on the temperature, which can range from warm to cool. When examined closely, the mature larva's face is marked with a white inverted "Y" with four dots, and the epidermis is rough or granular in texture (Prasanna et al., 2018). The FAO added that the larva pupates at a depth of 2 to 8 cm in the soil where it weaves a loose cocoon around itself by binding soil particles together with silk for 8–9 days before an adult moth emerges. Adult life lasts approximately 10 days, with a range of 7–21 days (FAO, 2020).

Since its arrival on the continent [first reported in West Africa in January 2016 (CABI, 2017a)], the pest has been spreading quickly throughout Africa (Kruger, 2017). Day et al. (2017) reported that the possibility of the Florida strain of Fall Armyworms being introduced to Africa is high (>90 percent), as it is limited to the eastern seaboard of the United States and the Caribbean islands. The FAO (2020) confirmed that the strong-flying insect pest has traveled to practically all of Sub-Saharan Africa within two years and is still spreading. The author noted that the FAW has been reported in Yemen, and the following countries in Asia: Bangladesh, Sri Lanka, Thailand, Myanmar, China including Taiwan, India, Indonesia, Philippines, Laos, Malaysia, Vietnam, Cambodia, Republic of Korea (South Korea), and Japan.

The Impact of FAW on Maize Production

In 2017, CABI estimated that in the absence of proper control methods, FAW could result in annual maize yield losses in 12 African maize-producing countries range from 8.3 tonnes to 20.6 million tonnes (enough to feed 40.8 million to 101 million people) valued at between USD 2.5 and USD 6.2 billion (Day et al., 2017). Mengestu (2017) stated that the impact of the FAW could rise up to about 30 percent or more losses in maize production at the country level. Rwomushana et al. (2018) conducted a household survey in Ghana and Zambia where 98 percent of farmers indicated that their maize fields were affected by FAW, with an average maize loss of 26.6 percent in Ghana and 35 percent in Zambia. The authors estimating the yield losses in financial terms across the two countries indicated that, the annual losses of maize in Ghana is valued at US\$177 million, and the annual maize crop in Zambia is valued at US\$159 million. The FAO (2020) suggested that FAW infestation is most likely to trigger population displacement from rural agricultural societies to urban areas, millions of the world's deprived people's food security and livelihoods are at risk.

FAW Control Methods

Hruska (2019) established that the rapid spread of the pest, combined with concerns about potential yield losses, has prompted a search for long-term management solutions. Mengestu (2017) noted that cultural, chemical, biological, and integrated pest control are all options for managing FAW. However, the writer argued that farmers who use the mechanical control (one of the cultural pest control methods) have a 54 percent success rate in controlling the pest. Farmers' exhaustion, correctly identifying the pest and

superstitions in some communities that crushing the larvae would cause the FAW to multiply are limiting factor in the effectiveness of mechanical control hence stifling its adoption. USAID (2018) added that the use of genetically modified (GM) seeds and crops, as well as judicious pesticide spraying, has helped to keep FAW under control. Although these and other care services are effective in the Americas, they are often prohibitively costly or unavailable to smallholders without government assistance or subsidies in Africa.

Day et al. (2017) argued that Integrated Pest Management (IPM), which employs a variety of control approaches, is the recommended approach to FAW control. The preservation of the pest's natural enemies is an important part of IPM. Prasanna et al. (2018) suggested that the aim of IPM is to economically eradicate insect species by using methods that cause the least amount of damage to the ecosystem, including humans. The authors added that a successful IPM strategy for FAW control would employ a range of integrated approaches such as host plant resistance (native and/or transgenic), biological control, cultural control, and safer pesticides to protect the crop from economic harm while minimizing negative impacts on humans, livestock, and the ecosystem. Though IPM is the preferred method, pesticides are often promoted by policy, whether deliberately or unintentionally leading several governments are supplying or subsidizing low-cost moderately hazardous pesticides in response to the appearance of FAW (Day et al., 2017).

Rwomushana et al. (2018) argued that the most common methods of FAW control is the use of pesticides. The authors added that pesticides are used by more farmers in Ghana than in Zambia, although it was used by fewer farmers in 2018 than in 2017. Sisay et al. (2019) studied the efficacy of synthetic

pesticides for controlling FAW, and observed that the use of synthetic insecticides was found to be successful, as it considerably increased Fall Armyworm cartapillar death, reduced leaf destruction, and increased yield. FAO (2020) argued that the rising use of hazardous pesticides is a major issue linked with FAW infestation., which provide farmers with an immediate remedy while also harming humans, livestock, aquatic life and environmental health. Hence the need to explore the use of a technology that minimizes the harmful effect of synthetic pesticides on humans, livestock, aquatic life and the environment. Annor-Frempong, Kwarteng, Agunga and Zinnah (2006) noted that ICTs-based technologies can be used in a cost-effective and realistic manner to reduce the effect of pesticides on farmers, livestock, aquatic life and the environment. Singh, Ahlawatat and Sanwal (2017) added that ICT-based technology transfer programmes are beneficial to farmers as it allows them to follow good agricultural practices, make better input decisions, and prepare their cultivation better with timely knowledge and realistic solutions to agricultural problems such as the FAW infestation.

Agricultural Technologies

In the agriculture sector, information and communication technologies (ICTs) are being deliberately used, the major economic industry in many African countries south of the Sahara, provide a great avenue for poverty alleviation and economic transformation on the continent (AfDB, 2012). Technology applications such as mobile banking, short message service applications (SMS), satellite data and drone applications are effectively providing agricultural practitioners such as extension agents with reliable and timely access to weather data, financial services, farm mapping and marketing

tools (Nuer et al., 2018). The FAO (2017) posited that close to (40%) of the people living on the African continent can access the internet. The FAO noted that the increased integration and adoption of information communication technologies in agriculture has reduced information and transaction costs, enhanced service delivery, developed new revenue streams, and conserved resources.

The use of technology in agricultural production has rapidly evolved in the past few years. According to Jack and Tobias (2017), the advancement of new technologies in agriculture has a potential to boost economic growth and reduce poverty in developing countries. For decades, technological innovations in the industrialized scientific world have benefited all categories of farmers through improved agricultural production (Rehman et al., 2016). Jack and Tobias (2017) posited that with more than half of working population in sub-Saharan Africa engaged in the agricultural sector, hence increasing agricultural productivity is an essential way to improve the livelihoods of smallholder farmers. Rehman et al. (2016) however, argued that in sub-Saharan Africa, smallholder farmers who produce (80%) of the food needs of the population are yet to make significant gains in their livelihoods due to limited adoption of technology.

The authors suggested that, majority of the smallholder farmers, women inclusive, have limited access to a myriad of modern tools needed to successfully increase food production. These tools include but not limited to agricultural information, crop management products, extension services, fertilizers, improved seeds, modern irrigation practices, mobile technology and postharvest loss solutions. These challenges faced by farmers are basically due

to the reason that agriculture on the continent is largely subsistence based. Uaiene (2009) however noted that, there is a necessity to increasingly transform agricultural production from the subsistence-based production towards a comprehensive commercialized production catalysed by productivity growth. This, according to Uaiene, is to help achieve the goals of food and nutrition security and poverty reduction in sub-Saharan Africa.

The agricultural transformation agenda in Africa is well documented and impinged on agricultural technology development and dissemination. For example in Ghana, the Medium-term national development policy framework: Ghana Shared Growth and Development Agenda (GSGDA) I, 2010-2013 provided the framework to accelerate the modernisation of the agriculture sector through the execution of the Food and Agriculture Sector Development Policy (FASDEP II) (MoFA, 2007) and the Medium-Term Agricultural Sector Investment Plan (METASIP) (MoFA, 2015). Underling the transformation agenda of the agricultural sector is the adoption of modernised agriculture technologies to improve agricultural productivity and economic growth (NDPC Ghana, 2010).

For instance, the long term objectives of the FASDEP II with respect to the development of the agriculture sector was for government to ensure that the stakeholders in agriculture are best positioned to benefit from emerging technological opportunities for improving agriculture in the country (MoFA, 2007). Also, METASIP I, an investment action plan to implement the medium term programmes of the country was promulgated in line with the ECOWAS Agriculture Policy and NEPAD's Comprehensive Africa Agriculture Development Programme (ECOWAP/CAADP) which outlines a unified

framework for supporting agricultural growth, rural development and food and nutrition security on the continent. It can be seen that the in Ghana, improving agriculture through modern agricultural technology has been promulgated in important policy documents as a major roadmap for harnessing agriculture potential as a means of reducing poverty, hunger and malnutrition (MoFA, 2007, 2010, 2015).

Jack and Tobias (2017) broadly defined agricultural technologies as “improved agricultural practices, crop varieties, inputs and other products like crop index insurance or innovative lending products (agricultural financing) to increase agricultural productivity and improve livelihoods (p. 1).” Arnholt (2001) opined that the revolution of these agricultural technologies has brought about new category of concept referred to as precision agriculture. Maru et al. (2018) sees precision agriculture as the use of more precise information created on the farmer’s field which differ from records from varied value chain actors that can be beneficial to a farmer but is collected, collated and disseminated by others as market information. Van Es and Woodard (2017) added that historically, precision agriculture as an established concept is aimed at crop production and improvement.

The National Research Council Report (1997, p. 2) defined precision agriculture as a “management strategy that uses information technologies to bring data from multiple sources to bear on decisions associated with crop production.” Lowenberg-DeBoer, Erickson and Vogel (2000) in support referred to precision agriculture as “using information technologies to tailor soil and crop management practices to fit the specific conditions found within an agricultural field” (p. 1). Arnholt (2001) asserted that precision agriculture

varies from several old technologies within agricultural sector but uses new trends in technological systems. Lowenberg-DeBoer et al. (2000) posited that precision agriculture combines technologies that depend on global positioning systems (GPS) and other new electronic devices to capture crop data and transforms the data into useful information for effective decision making.

The National Research Council (1997) indicated that the use of precision agriculture in farming involves three processes, namely, data capturing at an appropriate scale and frequency, data analysis and interpretation and management response to information through effective decision making and implementation of decisions at an appropriate scale and time. Lowenberg-DeBoer et al. (2000) and FAO and ITU (2018) concluded that information obtained from the use of precision agriculture technologies helps the farmer to implement site specific management strategies and plans effectively. The most significant impact of precision agriculture is on how management decisions address spatial and temporal variability in crop production systems (National Research Council, 1997).

Precision agriculture has multiple and varied components which may be adopted by farmers. According to Van Es and Woodard (2017), farmers who adopt several components of precision agriculture leverage the use of smart data and communication methods to optimise the output of field operations. Some farmers may also adopt a few of the components for a great effect (Arnholt, 2001). Van Es and Woodard (2017) posited that on-farm activities using precision agriculture are supported by geo-location equipment which include auto-steered and guided equipment, Global Positioning Systems (GPS), Geographical Information Systems (GIS), precision soil sampling, proximal and

remote spectroscopic sensing, yield monitors, unmanned aerial vehicles and variable rate technologies. The focus of this study is the use of unmanned aerial vehicles (Drone Technology) as a tool in precision agriculture for the control of FAW in Northern Ghana.

Unmanned Aerial Vehicles (Drone Technology): Definitions and Nomenclature

The record of the application of unmanned aerial vehicles (UAVs) is linked to its use by military. The legacy of unmanned aircrafts is traced to the military for warfare in the early 1849 (Hanssen, 2016; Hogan et al., 2017; Magistretti & Dell’Era, 2019). According to the authors the militaristic desire and capacity to scope one’s enemies in the battle field from long distances inspired military research and innovation into drone technology as both a weapon and information gathering device. Pricewaterhouse Coopers International Limited (PwC) (2016) posited that UAVs were used for commercial purposes in Japan at the start of the 1980s, when unmanned helicopters demonstrated efficiency in complementing piloted helicopters to spray insecticides on cultivated rice fields. During that period, remote controlled aircraft technology was very expensive and bulky to handle. The author however argued that improvement in technological capabilities, rule and regulations and capital injection and investment support have created avenue for several possible applications in agriculture, insurance, infrastructure, media and entertainment, security and law enforcement, transport, telecommunications and mining.

Field applications of UAVs usually referred to as “drones”, according to Probst, Pedersen and Dakkak-Arnoux (2017) have advanced tremendously in

the last few decades. The authors noted that the improvement in the technology has resulted in the fall of its cost in the market. In effect different types of drone devices for agricultural and other purposes are available in the market (Hogan et al., 2017; Puri et al., 2017; Torres-Rua, 2017). The Dictionary of Military and Associated Terms (2005) defined unmanned aerial vehicle as “a powered, aerial vehicle that does not carry a human operator, uses aerodynamic forces to provide vehicle lift, can fly autonomously or be piloted remotely, can be expendable or recoverable, and can carry a lethal or nonlethal payload.” The author noted that, semi-ballistic or ballistic vehicles, artillery projectiles and cruise missiles are not regarded as unmanned aerial vehicles. Ahirwar, Swarnkar, Bhukya and Namwade (2019) also defined a drone as “a flying device that can fly on a pre-set course with the help of an autopilot and GPS coordinates” (p. 2500). According to Tsan et al. (2019), drones deployed in agriculture are “remote-controlled pilotless aircraft that have many applications for agriculture field surveillance and remote diagnostics of agronomic conditions such as plant and crop diseases, water resources and soil quality” (p. 5). This study adopted the definition of drones by Tsan et al. (2019) since the authors provide clarity on the key components of the device such as for Agronomic problems such as plant and crop diseases and pests are monitored in the field and diagnosed remotely like the FAW which is the focus of this thesis.

The FAO and ITU (2018) indicated that like aircrafts, drones are flown and controlled remotely with the human pilot not on-board. Ahirwar et al. (2019) indicated that drone is piloted manually with a normal radio control in case of a dangerous situation or a fault. The authors added that, occasionally the term UAV is referred to as the complete system, together with ground stations

and video systems, and usually used as model planes and helicopters with rotary wings fixed on both sides. In terms of how it functions, Watts, Ambrosia and Hinkley (2012) stated that unmanned aerial systems are made up of the airplane elements, sensor payloads, and a control station on the ground. Ahirwar et al. (2019) added that the drone has four propellers (quadcopter) which are fixed and vertically positioned with independent and variable speed which facilitate a full range of movements. The smallest version of drones are usually complemented by ground-control stations made up of laptop devices and extra accessories little enough to be conveyed with the UAVs in backpacks, small cars and boats (Watts et al., 2012).

Puri et al. (2017) and FAO and ITU (2018) posited that drones are utilized in several fields including agriculture, disaster management humanitarian assistance and the military for security monitoring. Probst et al. (2017) indicated that progress in many fields, particularly in the batteries, imagery, miniaturization and remote communications have advanced the use of drones. Probst et al. posited that in 2016 the value of international drone trades reached approximately \$8.5bn. The global sales is expected surpass \$12bn by 2021. The Business Insider Intelligence indicated that over 7 million consumer shipments of drones were made in 2016. The author however projected that consumer shipments for drones is likely to grow exponentially to \$29 billion in 2021 (Business Insider Intelligence, 2016). Statistics released by PwC also showed that the value of drones deployed in all industries globally in 2015 was estimated to be above \$127bn (PwC, 2016).

The figures reviewed in literature indicated an upward growth of the use of drones in different industries. Torres-Rua (2017) indicated that the future of

efficient, effective and dynamic business world was drone technology. Probst et al. (2017) in support of the above noted that interest in both business and consumer drones was on upward trend in many industries especially in agriculture, with the development of new software and applications. Probst et al. added that the agricultural sector was expected to see increased use of drone technology in the not too distant future.

Types of Drones (UAVs)

There are many types of drones on the market used in agriculture and other fields. The FAO and ITU (2018) postulated that drones are different from conventional airplanes which are available in varied sizes, shapes, and patterns manufactured based on the take-off mass historically used to classify them. The take-off mass of a drone ranges from as low as ten grams to 25 kilograms and above (Raparelli & Bajocco, 2019). The FAO and ITU (2018) indicated that commonly produced categories of drones are two, 25 and 150 kilogram mass respectively. The authors argued that the categorisation of a drone is impinged on the age of the pilot, his/her competence (knowledge, skills and attitudes) in remote piloting, whether registration with the local Civil Aviation Authority is required, the necessity for electronic identification and the installation of a software like geo-fencing. The authors opined that heavyweight drones greater than 150 kilograms in mass are usually equated to conventional airplanes which have analogous safety, airworthiness, clearance and standards certification commitments which must be met by the operator.

Puri et al. (2017) noted that single pilot operated drones are considered as short distance flying devices, whiles that long distance flying ones are famous for flying at high altitude above sea level. Raparelli and Bajocco (2019)

indicated that the diversity and variation in the use of drones have affected the form, technical features, and the type of devices mounted on them. Some scholars have classified drones into two main groups; the Rotary Motor Helicopters and Fixed Wing Airplanes (FAO & ITU, 2018; Hogan et al., 2017; Puri et al., 2017). Raparelli and Bajocco (2019) also categorised drones as rotary wing, fixed wing and hybrid wing vehicles. The authors added that both the fixed-wing and rotary motor drones have their own strengths and limitations which merged to create the hybrid versions.

Fixed-Wing Drones

Fixed-wing drones are like model aeroplanes with a motor, battery, GPS and sensors (Puri et al., 2017). According to the Mississippi State University Extension Services (2019), the wings provide the drone with the lift therefore, the motor does not require battery power hover. This phenomenon allows the power of the battery to be utilised by the various accessories like the GPS and sensors on the device. Puri et al. (2017) posited that due to the strength of its battery, fixed-wing drones can be flown at greater speed varying from approximately 40-72 km/h to cover 500-750 acres of farm area in an hour. Mississippi State University Extension Service (2019) added that fixed-wing drones powered by superior 6-cell batteries made of Lithium-Polymer run on more power and allow the device to hover for over an hour on 1000 acres of farm land on a single battery.

The FAO and ITU (2018) argued that fixed-wing drones need a runway hence, commonly flown in automated manner. The Mississippi State University Extension Service (2019) saw this phenomenon as a disadvantage of the fixed-wing drone. The author argued that despite the fact that autopilots have

improved, the drone occasionally required a bit of experience to dock safely. Because of this underlying challenge, Puri et al. (2017) posited that fixed wing drones recorded more crashes than other types of drone.



Figure 5: Parrot fixed wing drone

Source: Parrot Drones SAS (2019)

Rotary Motor Drones

Puri et al. (2017) postulated that multirotor drones are similar to an helicopter but with several rotors. The authors noted that the rotary motor drones can fly and focus on particular on-farm problem with a constant speed. FAO and ITU (2018) added that rotary drones (copters) are flexible to pilot by hand because they require limited take-off and landing space, but have shorter flight duration. Due to the shorter flight duration, rotary motor drones can fly and land off securely in restricted areas without any challenges, an occurrence impinged on their limited battery lifespan (Puri et al., 2017). The Mississippi State University Extension Service (2019) posited that since the rotors empower the lift of the device, the battery life is significantly reduced. Hence, improved and upgraded batteries are being developed that would prolong hovering duration of multirotor drones in the field.

Puri et al. (2017) argued that the rotary motor drones are the best drones for beginner drone pilots. This assertion is supported by Mississippi State University Extension Service (2019) when it indicated that flying and landing

rotary drones are much easier for new pilots. Because the limited flying time of multirotor drones (usually between 15-20 minutes) enable new pilots to experience less crashes during flight landing.



Figure 6: Parrot rotor motor drone

Source: Parrot Drones SAS (2019)

Hybrid Drones

Hybrid drones were developed to harness the challenges of both the fixed-wing drones and multi motor drones. The FAO and ITU (2018) stated that hybrid drones are vertically shaped drones with take-off and landing (VTOL) systems for multipurpose operations programmed to maintain an efficient flight range without requiring a runway. Raparelli and Bajocco (2019) indicated that the take-off mass of hybrid drones varies from a few tens of grams to 25 and above kilograms.



Figure 7: Parrot hybrid drone

Source: Parrot Drones SAS (2019)

Areas of Drone Application

According to Hanssen (2016), drones are not only deployed as an integral part of military operations for battlefield surveillance but are also being applied in other other fields (Puri et al., 2017). Probst et al. (2017) identified four areas where drone applications are used. According to the authors, drones are used in agriculture, infrastructure, security and law enforcement and transport. FAO and ITU (2018) revealed that the United Nations has conducted field experiments using drones in several areas within its core mandate such as humanitarian emergencies and agriculture. Ahirwar et al. (2019) affirmed that drones are not only used in agriculture and law enforcement by the security agencies but also in industries such delivery services, disaster management, film and television industries, search and rescue and wildlife monitoring. The authors added that drones are also used as air ambulance in humanitarian fields.

The use of drones in the humanitarian field is fast growing. For instance, the World Food Programme (WFP) in collaboration with the government of Belgium led the first international workshop to deploy drones for humanitarian

crisis in the country (WFP, 2017). Also, the United Nations International Children's Emergency Fund (UNICEF) in partnership with the Malawian government has established a drone testing air corridor for humanitarian use aimed at testing three key areas (connectivity, imagery and transport) (UNICEF, 2017). The air testing corridor established in Malawi is with the aim of using it for humanitarian and development purposes is the first of its kind in Africa. Furthermore, the United Nations High Commission for Refugees (UNHCR) with the help of drones, supported displaced people on the African continent in countries such as Burkina Faso, Mali, Niger, Nigeria, South Sudan and Uganda. The drones were used to assess the needs of displaced refugees fleeing oppression and conflict situations. Drones have also been deployed in sports. Hanssen (2016) reported that coaches of National Football League (NFL) in the United State employed drone services to video game practice from the aerial view to peruse and analyse the performances athletes in detail. Hogan et al. (2017) reported of the use of drones for meteorological research in Australia.

The Global Search Engine, Google and the Food and Agricultural Organization of the United Nations have partnered to ensure that remote sensing are accessible, and efficient to promote precision agriculture (FAO, 2016). The collaboration according to FAO and ITU (2018), is to help stakeholders access high quality field data which is fundamental to promoting effective policies and programme towards the attainment of the SDGs by the year 2030. The review of literature revealed that drones are being used in different industries but not limited to infrastructure, transport services, insurance and actuarial science, media and entertainment, telecommunication, agriculture, security and mining. The focus of this study is however on application of drones in agriculture.

Agricultural Application of Drones

The application of drones in agriculture has been well documented (Barbedo, 2019; Barbedo & Koenigkan, 2018; Beloev, 2016; Handique et al., 2017; Hogan et al., 2017; Zhang & Kovacs, 2012). Probst et al. (2017) postulated that at the heart of meeting the growing global food demand lies the introduction of new, demand driven and cutting edge technologies in agriculture such as Artificial Intelligence, Big Data, Drones and Internet of Things ('IoT devices). The authors argued that these new technologies have been used to power and enhance existing rudimentary tools and methods with evidence of different applications already deployed on farms. Probst et al. (2017) added that new technologies pushing the expansion of precision agriculture is drone technology in recent years.

FAO and ITU (2018) posited that the application of drones technology in agriculture is growing at a very fast pace in crop production, disaster risk reduction, fisheries, forestry, early warning systems and wildlife conservation. Other areas of drones application in agriculture are soil and field analysis, crop health assessment, crop monitoring, crop spraying, monitoring irrigation equipment, aerial planting, weed identification, variable-rate fertility and monitoring cattle herds (Ahirwar et al., 2019; Barbedo & Koenigkan, 2018; Probst et al., 2017; Veroustraete, 2015). Torres-Rua (2017) also revealed that agricultural drones are used for biomass and yield estimation, soil moisture and evapotranspiration analysis, crop nutrient monitoring. Hogan et al. (2017) reported of farmers deploying drones for agricultural research in areas such as field crops and orchards management, grazed rangelands monitoring, lakes water level monitoring and ice sheets deposit in Greenland.

The legalisation, application and reliance on commercial drones in agriculture is expected to grow in the coming years (Barbedo, 2019; Barbedo & Koenigkan, 2018; Hogan et al., 2017). This is because according to Veroustraete (2015) and PwC (2016), the net market value of drones deployed in agriculture is projected to increase from \$32.4 billion in 2015 to \$77.59 by 2025. The increase in the market share of drones is expected to significantly make economic impact on revenues and job creation of agricultural entrepreneurs (Veroustraete, 2015). Puri et al. (2017) reported that the emerging agricultural drone market experience an annual growth rate of between 85-92%. This statistics according to Hogan et al. (2017) represent 19 percent of the large share of drones in all scientific fields of study.

Advantages of Agricultural Drones

As reported by Raparelli and Bajocco (2019), drones epitomise an important technological innovation of the last few decades due to its flexibility of use. The authors argued that the increasing application of the device in several scientific fields including agriculture has become one of the emergent outlook technologies lately. Hanssen (2016) opined that the on-farm proliferation of agricultural drones allows farmers to collect data in affordable, creative and safe methods than conventional ways. Hogan et al. (2017) added that the proliferation of drones in agriculture and other fields is driving down the price of the device. The authors argued that incorporating upgraded customizable applications for mobile devices (smartphones and tablets), miniature inertia measurement units (IMU, created for mobile devices), battery technology, GPS and the capacity to use cameras and sensors required for applications has provided enhanced flight duration, reliability, ease of use in

agriculture in addition to conveying, transporting and distributing farm products and facilities on farm and to clients (Raparelli & Bajocco, 2019). Puri et al. (2017) posited that drones provide competitive advantage as compared to other agricultural technologies in areas such as ease of use, tracing illegal farm activities, surveillance of crop yields on large plantations and precise monitoring and observation of farm locations difficult to reach by humans during field fire.

The prospect of deploying high resolution sensors and multispectral data for observing and understanding agricultural challenges in the form of crop categorization, health status, sunlight absorption rates and transpiration, signifies an important opportunity to control the application of fertilizers, pesticides and irrigation water, to optimize farm resources, reduce costs, increase the yield crops and the general quality of agricultural products is the game changer (Puri et al., 2017). Raparelli and Bajocco (2019) posited that the application of drones in agriculture is facilitated by the accurate positioning of the device, flexibility of use and its increasing agility in the agricultural field.

The Spraying Drone

The multi rotor motor drones are the UAVs usually used as spraying drones. Yallappa, Veerangouda, Maski, Palled and Bheemanna (2017) indicated that drone mounted sprayers are made up of a supporting frame, pump, pesticide tank, BLDC motors and Li-Po (Lithium polymer) batteries. Ononiwu, Okoye, Onojo, & Onuekwusi (2016) noted that the supporting frame is made of an aluminium frame to decrease the weight of the drone. Yallappa et al. (2017) added that the six BLDC motors are fixed to the hexa-copter aluminium frame to lift up to five kilogram payload capacity. The device is able to lift additional

payloads because of the use of 1800KVA motorised runners (Ononiwu et al., 2016).

Garre and Harish (2018) noted that two Li-Po batteries of six cells (8000mAh) are mounted to supply the required power needed to propel the system including the 10 litre capacity cylindrical shaped liquid container used to hold the pesticide and water mixture. Yallappa et al. (2017) posited that a 12 volts direct current motor pump is used to pressurise the pesticide solution to atomize the liquid into fine spray droplets which is discharged through the four nozzles. The Li-Po batteries are the standard battery choice for UAVs (Garre & Harish, 2018). The system is carefully integrated to guarantee that the aluminium frame could carry the payloads, the batteries and the pesticides tank (Ononiwu et al., 2016).

Yallappa et al. (2017) recommend that the pesticides tank, sprayer motor, the pump and supporting legs (landing gears) be mounted on a durable aluminium frame for safe landing and take-off. The authors concluded that with the assistance of a transmitter at the ground level and HD FPV camera provided at the front down side, the pilot is able to remotely control the drone mounted sprayer and monitor live field spraying operations. Ononiwu et al. (2016) posited that the pilot controls the drone mounted sprayer with a smart phone integrated with an android operating system through a user's command centre and a Graphical User Interface (GUI) on the phone.



Figure 8: The spraying drone in the field

Source: AcquaMayer

Characteristic Parameters of the Drone Mounted Sprayer

The characteristic parameters of the drone mounted sprayer is presented in Table (3). Lou et al. (2018) posited that the 10 litre capacity pesticides tank drone mounted sprayer has a dimension of $1.18 \times 1.18 \times 0.41\text{m}^3$. the authors noted that the device is fixed with four centrifugal nozzles with spraying width of 1.5 to 3m which can fly over crops to a height of between one to ten meters above ground level at a discharge rate of 200-800mL/min with an average speed of 5m/s.

Table 3: Characteristic parameters of UAV (Drone) sprayer used in the field experimentation

Parameter	Drone (UAV)
Dimensions (m)	1.18 × 1.18 × 0.41
Spraying width (m)	1.5–3
Nozzle type	Centrifugal nozzle
Nozzle numbers	4
Flow rate (mL/min)	200–800
Spraying height (m)	1–10
Tank capacity (L)	10
Spraying pattern	Low volume and high concentration

Source: Lou et al. (2018)

Pesticides Application using the Spraying Drone

The field application of pesticides is an essential part of present day agriculture and contributes to the quality and productivity cultivated and harvested crops (Hilz & Vermeer, 2013). Pimentel (2009) postulated that globally, more than three billion metric tons crop protection chemicals are used on annual basis. Pimentel however argued that, despite the large volumes of pesticide applied annually, plant pathogens, insects, weeds and pests destroy close 40 percent of all field and harvested crops.

The effective application of pesticides prevents crop losses up to about 45% of the global food supply (Cerda et al., 2017; Oerke, 2006; Oliveira et al., 2014). Hilz and Vermeer (2013) argued that there is however increasing environmental concerns due to increasing application of pesticides products by farmers because, drift of agrochemicals during field application can have an adverse effect on by-standers, livestock, near-by residents and aquatic and

terrestrial ecosystems. Generally, agricultural application of pesticides is in two forms, namely, aerial and terrestrial applications (Sammons et al., 2005).

Aerial application of drone technology as a capable tool for plant protection has emerged strongly in literature (Lou et al., 2018). Kirk (2000) postulated that drone application of crop protection products is convenient for the applicator and the environment because it improves the timeliness of the application. Hilz and Vermeer (2013) added that pesticides application using drones offers low drift, high speed application and extraordinary operational efficiency because it often produces liquid droplets released unto target crops. Huang and Thomson (2011) concluded that an important part of the use of drone for the application of pesticides in agriculture is the accurate set up of the spraying equipment through effective selection and configuration of spraying nozzles.

Several scholars have published works on the use of drones for pesticides, crop protection and crop improvement products application (Ajay et al., 2017; De Rijk et al., 2018; Garre & Harish, 2018; Giles & Billing, 2015; Hentschke et al., 2018; Lou et al., 2018; Mogili & Deepak, 2018; Spoorthi et al., 2017). A careful review of these published articles revealed that there is limited empirical data on the use of drones for the control of Fall Army Worm in Ghana. African Aerospace Online News Services (2017) reported that light jets and helicopters have been deployed in Zambia and other southern Africa countries to combat the African armyworms. According to the author during the 2016/2017 planting season, a projected 124,000ha out of 1.4 million ha of corn fields was destroyed in Zambia.

The statistics represent approximately 10 percent of the total cereal crops under cultivation in that country. Rambaldi and Guerin (2018) posited that the Zambian government established a fall army worm task force comprising officials of the Ministry of Agriculture, National Disaster Management and Mitigation Officials and the Zambia Air Force to distribute and spray pesticides to control the armyworm in designated hot spots across the country. The military services personnel deployed helicopters through aerial application to spray crop protection products to control the invasive insects (African Aerospace Online News Services, 2017).

Public Awareness and Knowledge of Drones

Eyerman et al. (2013) studied public perceptions and first responder concerns about unmanned aircraft and the human element revealed that the general public had fairly low level of awareness of drone technology. The authors reported that 44% of the respondents indicated that they had little to no experience with UAVs applications. Clothier, Greer, Greer and Mehta (2015) also found that lack of knowledge about drones, their abilities and different applications were the most mentioned themes among the general public in Australia. Reddy and DeLaurentis (2016) studied public perception in order to reduce the uncertainty about the use of drones revealed that 93% of the respondents from the general public had heard of drones through watching movies and following the mainstream media. On the other hand, stakeholders such as drone researchers in academic institutions, employees of government institutions, staff of aerospace and unmanned air craft industry, potential investors, drone test managers, pilots and UAS hobbyists heard about drones in trade literature and mostly from experience.

Aydin (2019) studied public acceptance of drones in the United States using the knowledge, attitudes and practice model and found that the public learned about drones from mainstream media and movies or television series which contributed to 80% of their knowledge of the technology. Tahir, Böling, Haghbayan, Toivonen and Plosila (2019) surveyed the use UAVs in Finland and Pakistan found that out of 187 participants, 78 had knowledge about drones whereas one hundred of them understood what drones are. Nine of the participants had however not heard about drone technology. Analysis of the literature indicated that there is limited awareness and knowledge about drone technology. Radecki and Jaccard (1995) noted that there is disparity between perception knowledge and actual knowledge which need to be pointed out. Aydin (2019) recommended that there is the need to measure the awareness and actual knowledge about drone technology and its broader applications because without knowing how much the public knows about the technology, it is difficult to develop strategies to effectively manage the revolution of drones.

Benefits of the Spraying Drone for the control of FAW

Spoorthi et al. (2017) and Mogili and Deepak (2018) revealed that due to the accuracy, speed and usefulness of its spraying operation, the use of UAVs for the control of FAW is becoming common. Hentschke et al. (2018) posited that drone application of pesticides is usually used in FAW stressed fields because of its accuracy, extraordinary speed and ability to cover large areas in a short period of time without human support. Lou et al. (2018) opined that drone mounted sprayers make crop protection against FAW in maize fields smarter, more precise and efficient with limited drift. Ahirwar et al. (2019) added that the use of UAVs for spraying minimises the effect of pesticides on

the environment and reduces stress on other organisms in the ecosystem. The authors noted that the drones can hover for longer hours allowing for reduced human exhaustion associated with other forms of FAW control (the use of Knapsack). Spraying with drones is estimated to be 40–60 times faster than spraying manually (UAV Systems International, 2019).

Giles and Billing (2015) indicated that drone application for the control of FAW has become an attractive proposition for most farmers and scholars due to its improved capability to apply pesticides in an extremely spatially resolved and timely manner, reduced pilot pesticide exposure and the ease of use. De Rijk et al. (2018) argued that employing drone spraying on FAW infested maize fields improves the coverage of the crop protection product on target insect without excessive spillage beyond reach of the target plots. De Rijk et al. noted that UASs employing visual tracking accessories permits the device to both differentiate FAWs from the fall of the leaf, pin points its position during manoeuvring to facilitate accurate spraying. Garre and Harish (2018) postulated that drone sprayers have come up as cheap means of controlling FAWs because it uses less amount of pesticides, it is easier to use and fit well with the way crop protection products are applied in the field. Spraying drones are effective in difficult terrains like small areas and hilly grounds where other ground spraying equipment cannot reach (UAV Systems International, 2019).

Mndzebele (2013) and Mairura (2016) argued that drone technology for the control of FAW can be perceived as a superior method of pesticide application because it offers innovative cultivation opportunities in the form of improved productivity and increased operational efficiency. The use of spraying drone technology for the control of FAW is consistent with existing operating

farm practices, previous experiences, values, beliefs and the requirement for the control of the vegetation devouring pest (Immorlica et al., 2007; Mairura et al., 2016). Mndzebele (2013) argued that the acceptance of drone technology for spraying pesticides for control of FAW will not require a change in attitude, belief and behaviour of the technology users. Therefore, Mndzebele concluded that the greater the compatibility of the spraying drone technology with the felt needs of controlling the effect of the FAW, the greater the acceptance and diffusion rate.

Several experiments have been conducted on the benefits of the drone mounted sprayer for pesticides application (Ahirwar et al., 2019; Hentschke et al., 2018; Lou et al., 2018; Mogili & Deepak, 2018; Spoorthi et al., 2017) and weedicides application (De Rijk et al., 2018). There is however limited empirical studies on benefits of drone for spraying pesticides for Fall Armyworm control in Ghana from the perspective of maize farmers in the northern part of the country. This study sought to fill the knowledge gap on the benefits of using spraying drone technology for the control of FAW through a survey. From the summary of reviewed literature, sixteen benefits of spraying drone technology will be used in the instrument of the study on a 10 point visual analogue scale.

The variables are drone technology applies exact quantity of pesticides to precisely kill the FAW with limited wastage, drone technology makes pesticide application easier with enhanced effectiveness through the use of less amount of chemicals, drone technology is beneficial because it is superior and fits well with other methods of pesticides application, the drone would not necessitate change in attitude, trust, and behaviour of farmers in Fall

Armyworms control, and the drone saves money and time, requires less labour and decreases harmful effect of pesticides on the environment.

Costs of the Spraying Drone for the control of FAW

Giles and Billing (2015) suggested that challenges of using drone for spraying pesticides are flight safety, environmental pollution, cost, payload and flight endurance limitations as well as regulatory actions by environmental and aviation departments of state. Mogili and Deepak (2018) posited that the use of spraying drones has come with it some challenges such as reduce quality of crop occasioned by limited field coverage during spraying and fields overlapping with outer boundaries crops. Longer distances between cultivated fields and spraying systems increases insecticide drift to adjoining plots thus reducing spraying efficiency (Faiçal et al., 2017). Mogili and Deepak (2018) added that the efficiency of the spraying components hosted on the drone increases through the pulse width modulation (PWM) controller during agrochemical applications, hence in comparison the effect of aerial sprayer application of pesticides becomes almost the same as field based sprayers when the PWM develops a fault. Hence spraying drones are less efficient and comes with additional cost compared to the use of other manual equipment especially when the spraying activities cover large areas (UAV Systems International, 2019).

Other challenges associated with use of the spraying drone for the control of FAW is the cost of procurement and maintenance of the device. UAV Systems International (2019) revealed that the cost and maintenance of agriculture drones are high. The author argued that the use of drones in the agriculture industry is currently being tested and explored hence production is being carried out on small scale synonymous with the high fixed cost. Despite

the high fixed and maintenance cost, Mogili and Deepak (2018) maintained that improvement is expected in the not too distant future. UAV Systems International (2019) reported that for instance the market price of the DJI Agras MG-1 drone mounted sprayer has witnessed more than 30 percent reduction since 2017 from \$14,999 to \$4,999. In order for smallholders to deal with the high cost drones, Probst et al. (2017) recommended that farmers can come together as a co-operative and purchase the equipment or acquire the drone services from drone/technology companies offering services to farmers.

Faïçal et al. (2017) noted that poor landscape or terrain and erratic weather conditions such as unexpected changes of wind speed and direction affect the quality service provided by the spraying drone, an assertion which is supported by Mogili and Deepak (2018). It can be observed that flying a drone requires competence and experience. Ahirwar et al. (2019) agreed that drone pilots need technical knowledge and skills to be qualified to operate the equipment.

Benefits and Costs of using Knapsack Sprayer for the control of FAW

Another very important and widely used tool for the control of FAW in Ghana is the Knapsack sprayer (Franke et al., 2010; Teka et al., 2012). Dandge and Ingole (2017) described a knapsack sprayer as a lever-operated portable unit sprayer which is extensively used for farm spraying activities. The authors noted that with the appropriate assembly and arrangement of its accessories, the knapsack sprayer can be used to apply fungicides, insecticides, herbicides and other crop protection products. It is the most common crop protection spraying equipment used by smallholders in developing countries due to its design,

versatility, ease of operation and cost (Ganehiarachchi, 2015; Mcauliffe & Gray, 2002; Sinha et al., 2018).

Ganehiarachchi (2015) indicated that it is called a knapsack sprayer because the operator conveys the equipment on his back during spraying, which allows the operator achieve higher accuracy. Faiçal et al. (2017) added that the spraying system must be very close the crops to reduce pesticides drift to neighbouring fields. Ganehiarachchi (2015) posited that the components of a knapsack sprayer are the tank (for holding 15 litres of liquid), an air compressing pump and a discharge hose connected to a valve and a nozzle. The knapsack sprayer has some benefits making it a reliable tool for FAW control by smallholder farmers.

Ganehiarachchi (2015) identified six important benefits of knapsack sprayer.

These are:

1. useful for developing high pressure spraying with little effort,
2. easy to convey on the back of the operator due to its light weight.
3. economical with high work rate
4. can be operated with both hands
5. simple for spraying pesticides and
6. very easy to maintain (p. 204).

Despite the benefits of the knapsack sprayer, some costs are also documented in the literature. Sinha et al. (2018) revealed that fatigue is one of the challenges involved with the use of the knapsack sprayer. The authors also opined that the operator may find it difficult maintaining a continuous pressure on the pump due to stress and fatigue. Sinha et al. indicated that the operator starts experiencing the fatigue on the left clavicle region, to lower back, neck,

left thigh and right clavicle. The fatigue associated with use of knapsack increases because the operator has to carry the equipment on his back and ensure continuous pumping during pesticides application (Dandge & Ingole, 2017). Crop damages are incurred when using knapsack sprayers. Faiçal et al. (2017) found that the spraying exercise is usually slow because the liquid has to have direct contact with the crops which reduces the cultivation area of smallholder farmers. The author added that sometimes the direct contact of the liquid damages healthy crops. The damaging of healthy crops is highly influenced by the operator's skills (Ganehiarachchi, 2015).

In another breath, Mcauliffe and Gray (2002) also noted that lack of pressure control by the operator can cause inconsistent pesticide solution flow dosages, variable spray droplet sizes and pattern which ultimately affect spray coverage and pesticide performance in the field. The author added that the inconsistent pressure can influence the spray drift which will worsen the operator's exposure to the pesticide. Though the knapsack sprayer has some advantages, the demerits need to be considered by farmers when using it for the control of the FAW.

Some authors have conducted studies on pesticides application with use of the knapsack sprayers (Dandge & Ingole, 2017; Faiçal et al., 2017; Franke et al., 2010; Ganehiarachchi, 2015; Mcauliffe & Gray, 2002; Sinha et al., 2018) and use of drone mounted sprayer (Ajay et al., 2017; Giles & Billing, 2015; Hentschke et al., 2018; Spoorthi et al., 2017). A comparative study has been conducted on the use of the spraying drone and the boom sprayer (Lou et al., 2018). There is however limited empirical data on the comparative study of the use of drone technology and knapsack sprayer for control of FAW. From the

standpoint of maize farmers in Northern Ghana, this study aimed to evaluate the costs and benefits of using a drone mounted sprayer vs a backpack sprayer to manage FAW.

Scale Development

Measuring abstract variables has been an issue engaging the thoughts of Social scientists and Agricultural extension educators for many years. However Krabbe (2017), posited that much has been accomplished with more sound methodology for development and application of instruments to measure subjective agricultural outcomes. Agostini, Nosella and Teshome (2019) suggest that several measurement scales have been developed to measure attitudes, techniques and interventions in diverse scientific studies. The fundamental activity of any scientific inquiry is measurement, because Morgado, Meireles, Neves, Amaral and Ferreira (2017) maintain it enables researchers to develop knowledge about people, objects, events and processes. Measurement involves a multifaceted and partially subjective concept of capturing many characteristics that are not directly observable (DeVellis, 2017; Krabbe, 2017).

Morgado et al. (2017) agree that measurement scales are helpful tools used to attribute scores in numerical dimension to variables that cannot be directly measured. These concepts as Krabbe (2017) puts it often lack precision and clarity, due to their ambiguous nature and hence need to be translated from abstract form to be made measurable in the form of variables. Whiles some variables in agricultural extension education are clear, precise with universally agreed definitions, others are less obvious and not directly and reliably measurable. Such unobservable features are inferred and described as postulated

constructs, latent traits or latent factors (Krabbe, 2017). These imaginary concepts which are believed to exist are measured by latent variables (Morgado et al., 2017; Tay & Jebb, 2017).

Latent variables are presumed to cause other items to take on certain values of specific subject at a specific time (Pett et al., 2003). DeVellis (2017) reveals that a latent variable has two key features; it is latent rather than manifest and the construct is variable instead of constant meaning its strength or magnitude changes. Latent variables are used in many social scientific studies. Factor analysis and structural equation modeling are two most widely applied latent variable models. This study used both factor analysis and structural equation modeling to explain the propensity of maize farmers to accept drone services for Fall Armyworm control in Northern Ghana. Behavioural intention of the maize farmers, who are the primary data source (unit of analysis) of this study (DeVellis, 2017).

In the absence of a standard unit of measurement, scholars have developed several methodologies to measure latent variable. These methodologies which are known as scaling models can translate subjective perceptions into quantitative measures (Krabbe, 2017). Scaling models are used to scale both subjects and objects together or individually (Morgado et al., 2017; Tay & Jebb, 2017). Krabbe (2017) argued that one of the scaling modeling used for scaling only subjects (maize farmers) is the Likert scaling. The Likert scaling was adopted for measuring the latent variables of this study. In using Likert scaling, maize farmers were presented with a list of statements about single topics and with help of enumerators instructed to respond to every statement

(Likert items) in terms of their degree of agreement or disagreement (Krabbe, 2017).

Likert Scales used in this study

The peruse of literature show that scholars have little agreement about the use of Likert scales in quantitative research. Whiles some authors argue that Likert scales are ordinal in nature (Borg, 1998; Borg, 1962), others suggest that the scale is interval in nature and can be used for parametric analysis (Allen & Seaman, 2007; Armstrong, 1987; Dunbar et al., 1992; Glass et al., 1992; Green et al., 2003). The issues associated with the decades of debate on Likert-type scales and responses are not about the appropriate statistical tools to use to analyse data measured on the scale but as Pell (2005) puts it, is in accurately understanding the nature of the analyses and inferencing the outcome of the results. Jamieson (2004) in her article published in the Journal of Medical Education posited that Likert scales are ordinal in nature (meaning it produces rank order data), therefore should be analysed using non-parametric statistical tools. Pell (2005) in response to Jamieson's article outline three important facts that make Likert scales (groups of items) interval in nature contrary to individual Likert items which are ordinal in nature and thus Likert scales can be analysed using robust and advanced level parametric statistical techniques with all its associated benefits. The views espoused by the intervalist according to Bishop and Herron (2019) is because parametric statistics are generally perceived as more robust than non-parametric.

Knapp (1990) argued that the simplicity of non-parametric techniques (for instance, the signed-rank test) biases some researchers to assign a greater recognition to parametric analyses than to non-parametric. It is worth noting

that the objective of this study is to produce valid results useful for advancing the field of drone technology for the control of FAW, hence, to make valid statistical inferences need the use of valid statistical analyses (Bishop & Herron, 2019). Studies on the nature of Likert scales (contrasted with single Likert items) have shown that Likert response format yields empirically interval data and can even approximate ratio data (Carifio & Perla, 2008, 2007). This study aligns to the intervalist perspective of Likert scaling to measure different variables to explain the tendency of maize farmers to accept drone services for Fall Armyworm control in Northern Ghana.

In the view Carifio and Perla (2008), all true Likert scales should include multiple-questions on a given topic of interest where the cumulative score reflects the measurement scale. The authors also argue that, a minimum of six items are needed to produce a reliable construct. Items on this scale can have responses which may or may not be Likert-type responses (Bishop & Herron, 2019). Most critics of “Likert Scales” confuse response format from the actual multiple-component scale (Likert scale). The individual items on a scale are not independent and isolated but are connected in a manner to produce a single unified outcome (Carifio & Perla, 2008, 2007; Krabbe, 2017). The unified construct is more reliable and reflects the underlying measurement better than the individual items on their own (Bishop & Herron, 2019). Therefore, Carifio and Perla (2008, 2007) argued against statistical analysis of individual items, indicating that summative evaluation of Likert scales produce interval or ratio data.

The assertion was supported by (Krabbe, 2017) when he posited that a defining nature of Likert scales is that they have response categories that have

distinct cut-off points which assume linearity and equal intervals between the points. Likert scales commonly used by Agricultural extension scholars include numeric ratings and adjectival rating scales (Harpe, 2015). Likert adopted five options with a neutral category in the original version (Likert, 1932). However, the response format has been expanded by scholars to different numbers of response categories including eliminating the neutral option (Cohen et al., 2007; Krabbe, 2017). Over the years, the use of Likert's technique has metamorphosized from measuring respondent's level of approval or agreement to frequency (for example, Never, Sometimes, Often and Very Often) or importance (Not at all important, Unimportant, Somewhat important, and Very important) (Harpe, 2015). Uebersax (2006) noted that recent examples are referred to as Likert-type scales because individual items are summed and presented horizontally with equally spaced integers and presented with labels that are approximately equal in spacing.

Simon and Goes (2013) noted that Likert-type scales are utilized as interval scales in social science research, provided scale items have at least five categories or preferably seven or more. Simon and Goes argued that the fewer the number of categories on the scale, the more likely the scale would deviate from assumptions of normality required for many advanced statistical analysis. Uebersax (2006) recommend that reseachers use a type of Likert-type scale referred to as discrete visual analogue scale where printed format infers a specific metric relationship among the response levels with adjectives at the extreme ends. It is discrete because only pre-specific levels might be given by the respondents. This study adopted the discrete visual analogue scale. Interval

scales have an arbitrary zero, hence zero was added to the scale (Carifio & Perla, 2008, 2007; Harpe, 2015).

Empirical Review of Farmers and Farm Related Characteristics

Attempts have been made by some scholars to evaluate the degree of innovation uptake (adoption rate) among adopters of innovations found that adoption of technologies or innovation is known to be influenced by many factors. Rogers (2003) posited that in a social system, adoption of a new technology or innovation does not occur at the same time; rather, it is a cycle in which certain people are more likely to adopt the innovation than others. LaMorte (2019a) argued that people who adopt an innovation early have different characteristics than those who adopt it later, hence when promoting a technology to a target audience, it's critical to consider the characteristics of that population that will aid or impede adoption.

Nmadu, Sallawu and Omojeso (2015) studied the socio-economic factors which affected adoption of innovations by farmers in the Ondo State in Nigeria and found that the adoption technologies were positively influenced by sex and level of education of the farmers. Issa, Kagbu and Abdulkadir (2016) also analyzed the socio-economic factors that influenced farmers' adoption of improved maize production practices in Ikara Local Government Area of Kaduna State, Nigeria and reported that the adoption of improved maize production and practices was strongly linked to the size of the farm cultivated to maize by the farmers. In a related study, Mmbando and Baiyegunhi (2016) reported that off-farm revenue, access to extension services, access to credit, membership in farmer based organizations and involvement in on-farm

demonstrations are factors which affected the adoption of improved maize varieties in the Hai District in Tanzania.

Bilaliib Udimal, Jincai, Mensah and Caesar (2017) found that Farm size, credit access, on-farm demonstration, tractor ownership, and family labour all had a positive and statistically meaningful impact on (Nerica) rice technology in Northern Ghana. Donkoh, Azumah and Awuni (2019) revealed that education, household size, experience, farm size, sex, and the age of the farmer are all important socioeconomic variables influencing the adoption of improved agricultural technologies among rice farmers in Ghana. Farm size has a major positive and negative impact on adoption chances, which may represent two opposing viewpoints in the literature. Farm size is merely a proxy for financial capability, because larger farms have more money to invest in environmentally friendly technology (Serebrennikov et al., 2020).

Esabu and Ngwenya (2019) studied the socio-economic factors influencing adoption of conservation agriculture in the Moroto District in Uganda and found that farmers' decision to adopt or not adopt conservation agriculture was influenced by access to extension services and credit, as well as sex. Sinyolo (2020) found that female farmers were more likely than their male counterparts to adopt improved maize varieties, invest more to ensure household food security, and benefit more from adoption in a study of technology adoption and household food security among rural households in South Africa. Martey, Etwire and Kuwornu (2020) analyzed the economic impacts of smallholder farmers' adoption of drought-tolerant maize varieties and found that access to seed, agricultural extension services, labour supply and farm household location all play a role in drought tolerant maize adoption in

Northern Ghana. The authors also reported that adoption of drought tolerant maize had a positive effect on yield and commercialization intensity.

Empirical review on the factors that influence the adoption of technologies were further reviewed to provide an understanding of the important characteristics to enable agricultural extension agents to pay particular attention to the various groups in the adoption of drone services for Fall Armyworm control in Northern Ghana. Farmer characteristics focused on sex, age, number of years of farming experience, marital status, and type and level of education. The review also focused on farm related features such as farmers' access to agricultural extension and training, farm size cultivated to maize, yield of maize in Mt/ha, income received in GH¢, land holding arrangement, and main sources of household income.

Sex of Farmers

There is considerable variances between male and female farmers across the length and breadth of Ghana (Ghana Feed The Future Agriculture Policy Support Project (APSP), 2014). Abdulai, Nkegbe, and Donkor (2017) and Abdulai et al. (2018) studied maize farmers in Northern Ghana and reported of more male involvement in the production of maize than females. Anang (2018) studied farmers in Northern Ghana and found out that majority (78%) of the 300 farmers surveyed were males whiles (22%) were females. Tasila Konja, Mabe and Alhassan (2019) also found that eight out ten of the farmers sampled were males.

Ghana Feed The Future APSP (2014) in a gender baseline study in the Guinea Savannah ecological zone in the country revealed that females form majority (84%) of farmers sampled for the survey. Wongnaa and Awunyo-Vitor

(2019) found out that (88.2%) of farmers sampled were men while (11.8%) were women which contradict the findings of Ghana Feed The Future APSP (2014). The high number of males reported by the scholars imply that maize production is a male-dominated enterprise among the farmers in Northern Ghana (Anang, 2018; Wongnaa & Awunyo-Vitor, 2019).

Age of Farmers

Makate, Makate, Mango and Makate (2017) investigated livelihoods of smallholder farmer in Southern Africa and found out that farmers are getting older. The mean age of maize farmers in communities in Northern Ghana was reported to be between 40 – 45 years (Abdulai et al., 2018, 2017; Anang, 2018; Tasila Konja et al., 2019). Similar findings were reported by Wongnaa and Awunyo-Vitor (2019) that the majority (64%) of farmers surveyed are between 18 and 45 years age bracket with three out of every ten between 46 to 70 years. Wongnaa and Awunyo-Vitor also revealed that age of farmers sampled in the Transitional and Coastal zones were not different from Guinea Savannah zone.

It can be deduced from the literature that farmers involved in maize production in the Northern belt of Ghana are reasonably old (Wongnaa & Awunyo-Vitor, 2019). Bempomaa and Acquah (2014) asserted that this phenomenon may influence the efficiency of maize production in the study area. Onubuogu, Esiobu, Nwosu and Okereke (2014) and Mabe, Donkoh and Al-hassan, (2018) held the view that young farmers are likely to embrace new technologies to improve productivity of maize production compared to older farmers. Abdulai et al. (2018) argued that typical farmers in Northern Ghana are between the ages of 15 to 60 years, hence, are regarded within the economically active population as prescribed by Ghana.

Years of farming experience of Farmers

Bempomaa and Acquah (2014) surveyed maize farmers and recorded that the number of years of farming experience in maize production was between two to 52 years with mean of 18 years. Abdulai et al. (2017) and Abdulai et al. (2018) reported that that years of experience in agriculture of maize farmers surveyed was between one and 40 years with mean experience of 8.72 and 10.33 years respectively. Tasila Konja et al. (2019) also found out that the average years of experience of farmers was 14 years.

Similar finding was also reported by Wongnaa and Awunyo-Vitor (2019) when they reported that maize farmers in the Northern part of Ghana are very experienced with an average of 18.6 years of experience in maize production. Wongnaa and Awunyo-Vitor further noted that apart from farmers in the Forest region who had an average of less than ten years of farming experience, farmers in the Transitional and Coastal belts of Ghana recorded high levels of farming experience. Farmers having a significant amount of farming experience have enhanced knowledge to efficiently allocate material and financial resources and are better positioned to run an efficient and profitable farming enterprises (Esiobu et al., 2014; Onubuogu et al., 2014). Wongnaa and Awunyo-Vitor (2019) posited that farmers with high years of farming experience are likely to have higher yields since they have the required experience to predict the appropriate agronomic activities for efficient production of maize.

Type and level of education of farmers

Esiobu et al. (2014) posited that farmers exposed to higher level of education have an additional benefit with respect to achieving yield in maize

production. Bempomaa and Acquah (2014) and Anang (2018) studied maize farmers in Ghana and found out that averagely farmers surveyed spent approximately seven and six years respectively in school. Abdulai et al. (2017) and Abdulai et al. (2018) confirmed that farmers in the Northern belt of Ghana possess moderately low level of education. Wongnaa and Awunyo-Vitor (2019) also studied farmers and concluded that close to seven out of ten of the farmers sampled had no formal education while almost (20%) had between primary and Junior High School level of education. Similar findings were recorded by Tasila Konja et al. (2019). The review shows that the farmers sampled in the various authors had formal education of approximately up to primary level.

Marital status of farmers

Makate et al. (2017) examined farmers in southern African and revealed that majority (83%) of farmers sampled were married compared to (17%) who were single. Similar findings were revealed by Tasila Konja et al. (2019) who studied farmers in Northern Ghana reported that close to eight out of ten farmers sampled were married. Some authors have posited that married maize farmers are likely to have access to enhanced land tenure systems and large household inputs which are customarily owned for advanced maize production (Mabe et al., 2018; Onubuogu et al., 2014).

Farmers' access to agricultural extension and training services

Bempomaa and Acquah (2014) revealed that averagely farmers in Northern Ghana receive agricultural extension and training services once every planting season. The number of extension visits received by farmers sampled

by Abdulai et al. (2018) ranged between one and four times per planting season with an average of three times. Tasila Konja et al. (2019) also reported that (36%) of farmers sampled did not receive extension visits or trainings whereas (64%) received extension visits seasonally. Similar findings were also reported by Wongnaa and Awunyo-Vitor (2019) who found that six out of ten farmers surveyed recorded one or more agricultural extension and training services every planting season. Tasila Konja et al. (2019) asserted that increasing farmers' access to agricultural extension services enables them to receive education and training on new agricultural technology innovations to increase their production. It is worth noting that agricultural extension system functioning efficiently is important for improving the production of food crops and offer a great avenue for smallholder farmers to exit poverty (Gautam, 2000; Everson, 2001).

Farm sizes of maize cultivated by farmers

There is a general assertion that farmers in rural communities in Northern Ghana cultivate small farm holdings. The assertion was confirmed by Addai and Owusu (2014) when they found that the mean farm sizes of farmers surveyed was 1.71ha. Abdulai et al. (2017) studied maize farmers and found that the farm sizes ranged between 0.2ha to 24ha with mean farm size of 3.21ha. Abdulai et al. (2018) in separate study recorded an average farm size was 1.76ha. Similar findings were reported by Wongnaa and Awunyo-Vitor (2019) who revealed that mean farm size of maize cultivated by farmers in the Guinea Savannah agro ecological zone of Ghana was 2.7ha.

The review revealed that indeed farmers in rural communities in Northern Ghana are working on smaller farm holdings. This deduction is

supported by Nyanteng and Seini (2000) who noted that more than 90 percent of staple food produced in Ghana came from smaller farm holdings of 3ha or less. It is therefore not far from right to infer that maize production in the study area is on small scale (Wongnaa & Awunyo-Vitor, 2019).

The farmers can also be classified as smallholder farmers as noted by Chamberlin (2007) that small land holding is the most direct indicator of who smallholders are. This assertion is confirmed by MoFA (2017) when it posited that, smallholder farmers dominate Ghana's agricultural sector, with about (90%) of them cultivating less than 2ha of farm land. The situation of farmers cultivating small land holdings is not only limited to Ghana but also prevalent in some African states. This is because smaller farm holdings were recorded in Kenya (Mulwa et al., 2009), Nigeria (Onubuogu et al., 2014) South Africa (Makate et al., 2017) and Zambia (Abdulai & Abdulai, 2016).

Yield of maize

Abdulai et al. (2017) studied the yield of maize farmers in Northern Ghana and found that the mean maize yield recorded by farmers was 2.0Mt/ha. Similar findings were also recorded by Abdulai et al. (2018) who surveyed maize farmers in same region of the country. Wongnaa and Awunyo-Vitor (2019) also reported that mean yield of maize recorded by smallholders in the Savannah and Transitional regions was 2.2Mt/ha and 4.2Mt/ha respectively. The findings indicated that smallholders in the Transitional zone recorded relatively higher yield compared to their counterparts in Savannah zone.

It is worth noting that the maize yields recorded by the afore authors fall short of the projected possible yield of 5.5Mt/ha in Ghana (MoFA, 2017). The yields of maize recorded by farmers in Zambia (6.3Mt/ha) are relatively higher

than yield obtained by farmers in Ghana (Abdulai & Abdulai, 2016). The lower yields of maize recorded by farmers in Ghana can be attributed to the effects of climate emergency (AGRA, 2018) and the incidence of FAW which according to Day et al. (2017) accounted for 45% of yield losses in 2017.

Adu et al. (2014) posited that maize yield of 4.5-7.5Mt/ha can be obtained if farmers adopt the good agronomic activities recommended by the Savannah Agricultural Research Institute of Ghana. The recommended good agronomic practices include fertilizer application complemented with organic manure for soil nutrition and conservation management, crop rotation, intercropping with leguminous crops, planting improved seeds, weed control and ploughing the soil before planting. It can be deduced that farmers who adopt these practices would improve yields in the midst of the challenges of global climate emergency.

Income Received from the Sale of Maize

Abdulai et al. (2017) found out that the mean earnings received maize by farmers from the sale of was GH¢ 1234.74. Similar mean income of GH¢ 1,229.50 for the same quantity of maize was reported by (Abdulai et al., 2018). In a free market economy like Ghana where prices of agricultural commodities fluctuate due to the period of the year when the commodities are sold, the revenue expected from the sale of the will be affected by the time the commodity was sold (Esoko Ghana, 2019).

Land Holding Arrangement

Farmers operate different land holding arrangements in Ghana. Amanor-Boadu et al. (2015) in the agricultural production survey for the Northern Regions of Ghana found that majority (72%) out of the 1,120 farmers sampled indicated to owning the farm lands they work on. The rest of the farmers indicated that their farm lands were family owned (24%), community owned (3%) and other forms ownership (1%). The authors noted that the distributed control over land is a deviation from the conventional perceptions about land ownership in Ghana, where majority of land is under customary or community ownership.

Diaw (2005) indicated that rural lands in Ghana are predominantly administered by indigenous ownership principles mixed with national law and occasional private ownership. Amanor-Boadu et al. (2015) noted that individual outright ownership of land in Northern Ghana does not indicate unregulated ability to dispose off the land through sale due to the strong relationship community people have with land. Bugri and Yeboah (2017) posited that there is renewed interest by individuals to invest in land for agricultural purposes in recent years in Ghana.

Main Sources of Income by Farmers

It has been recognised that rural farmers engage in other activities in order to improve their household income. In Ghana, the ability of farming alone to sustain rural livelihoods of farm households in most parts of Northern Ghana is very much in doubt (Baidoo et al., 2016). Dary and Kuunibe (2012) in their study revealed that out of the 172 farmers sampled, (83%) reported to engage in other activities as alternate source of income while 17% depended on

farming as the only source of income. Among the farmers engaged in other income generating activities, 79% were engaged in a single activity while 21% were involved in two or more activities. The off-farm activities recorded by Dary and Kuunibe (2012) included blacksmithing, carpentry, masonry, butchery, tractor operating and motor cycle repairs.

Anang and Yeboah (2019) found that 43% of the farmers sampled earned revenue from off-farm activities such as petty trading and official jobs. Baidoo et al. (2016) also recorded livestock production as another source of household income by farmers in Northern Ghana. Considering that off-farm activities provide alternative sources of income for crop farmers, Sienso, Mabe and Mbeah (2015) recommended that stakeholders in agriculture including extension agents, NGOs, opinion leaders and policy makers should implement programmes aimed helping farmers diversify farming into alternative sources of income to support their households.

Conceptual Framework of the Study

The conceptual framework of the study was developed based on the Theoretical and empirical reviews of the literature used to support this study. In order to understand the inter-relationships between farmers' awareness of drone technology, the benefits of applying, the cost and benefits and the intention or desire of the farmers to adopt the drone spraying services for control of FAW, the challenges associated with the rapid spread and damage caused by the invasive pest need to be understood. The incidence of the FAW in Ghana is threatening agricultural production especially the production of maize, an important staple and food security crop in the country. The framework of the study was guided by the the Diffusion of Innovation Theory by Everett Rogers

(1995), the Theory of Reasoned Action by (Fishbein & Ajzen, 1975), the Theory of Planned Behaviour (Ajzen, 1991) and the extended Technology Acceptance Model TAM3 (Davis, 1989; Venkatesh & Bala, 2008; Venkatesh & Davis, 2000).

From the literature, it can be seen that agricultural enterprises are briddled with a myriad of challenges including pest infestation. One of such pest is the FAW which since it was reported in Ghana in 2016 has racked havoc on maize production in the country significantly affecting the yield of the crop (Day et al., 2017; Rwomushana et al., 2018). The literature points to the fact that, the application of technologies like drones improve agricultural production including pest control (Mbuya et al., 2018; Probst et al., 2017; Rambaldi & Guerin, 2018). However, research has shown that the adoption of such technologies in agriculture is limited in Africa including Ghana (Bawa, 2019; Jack & Tobias, 2017). The study sought to examine farmers' acceptance behaviour of drone technology for the control of FAW in northern Ghana.

In order to achieve the objectives of the study, the awareness of the farmers on drone technology was assessed together with their perception of the benefits of deploying the technology for the control of FAW. This was situated within the context of Rogers (1995) who posited of five characteristics of technology which influence the adoption of technologies namely; relative advantage, compactibility, complexibility, triliability and observability. The study also looked at how the farmers perceived the economic costs and benefits of adopting the drone technology as compared with the knapsack sprayer in the local communities of the farmers.

The study compared the perception of the farmers on the costs and benefits of adopting the drone which is a modern tool developed by the western world as compared to their use of an existing traditional tool, the knapsack sprayer for spraying pesticides for the control of FAW. The study also examined farmers' intention of adopting the drone technology for the control of the invasive pest using the technology acceptance model TAM 1 developed by Davis (1989) and extended by Venkatesh and Davis (2000) into TAM 2 and Venkatesh and Bala (2008) into TAM 3 which have its root in the Theory of Reasoned Action and the Theory of Planned Behaviour. TAM 1 posited that behavioural intention of the farmer to adopt a new technology is positively influenced by the attitude towards the use, PU, and PEOU of the technology.

The behavioural intention is the desire or willingness or propensity of the maize farmers to adopt the drone for spraying pesticides for control of FAW whereas attitude towards use is evaluative judgment of a maize farmer in adopting the drone technology for the application of pesticides for the control of FAW (Davis, 1989; Venkatesh & Davis, 2000). Attitude and intention are greatly influenced by perceived usefulness and ease of use. Perceived usefulness is the extent to which a maize farmer believes that drone technology for pesticides application for the control of FAW will enhance productivity or performance (Davis, 1989). The perception of the ease of use of the drone technology is driven by cognitive instrumental variables such as perceived ease of use, subjective norm, image, job relevance moderated by output quality and result demonstrability (Venkatesh & Davis, 2000).

Perceived ease of use is extent to which a maize believe that utilizing drone spraying services for pesticides application for Fall Armyworm control is

simple and easy (Davis, 1989). Perceived ease of use is also driven by four anchor variables, self-efficacy, anxiety, playfulness and perception of external control and two adjustment variables, perceived enjoyment and objective usability. In the framework of this study, adjustment variable, objective usability was eliminated from the model. Also, usage behaviour which is influenced by intention was also removed from the model. The study's conceptual framework is illustrated in Figure (9).

Chapter Summary

The chapter was made up reviewed literature related to the acceptance of drone technology services for the control of FAW in selected districts in Northern and North East regions of Northern Ghana. It also presented the theoretical frameworks which underpinned the study, namely the Diffusion of Innovation Theory, the Theory of Reasoned Action, the Theory of Planned Behaviour and the Extended Technology Acceptance Model (TAM3). Concepts related to drone technology and FAW were also reviewed. The chapter ended with empirical review on the background and farm-related characteristics of the farmers and conceptual framework derived from the review that guided the study.

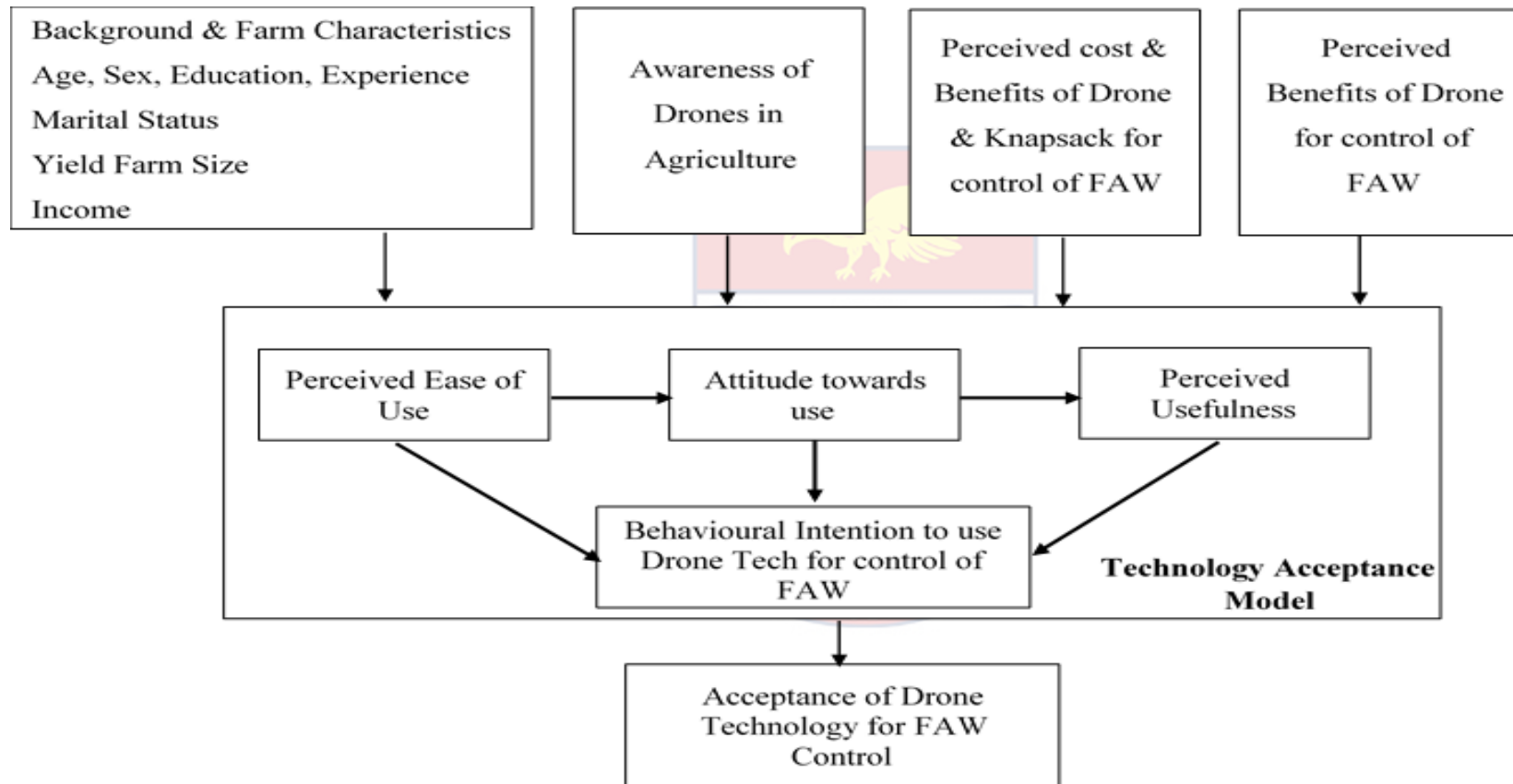


Figure 9: Conceptual framework of the acceptance of drone technology for control of FAW

Source: Adopted and Modified Extended Technology Acceptance Model by Davis (1989)

CHAPTER THREE

METHODOLOGY

Introduction

The chapter presents and discusses the methods and processes utilized in conducting the study. Description of the study area, philosophical underpinnings, the research approach and designs, population of the study and sampling techniques, procedure and sample size. Other areas covered in the chapter are instrumentation, determination of validity and reliability of the instruments, data collection procedure, data analysis and ethical considerations.

Study Area

The study was conducted in the West Mamprusi municipality of the North East region and Tolon and Mion Districts of the Northern region. The two study regions together with Savanna, Upper East and Upper West regions constitute the Savannah Agro-ecological zone of Ghana (Baidoo et al., 2016; Bawa, 2019; Mangnus & van Westen, 2018). Greater number of the farmers in the northern part of Ghana are smallholder farmers (Chamberlin, 2007) with crops and livestock farming as the main commercial and income generation activities undertaken by the households (Baidoo et al., 2016). According to Anang (2018) the smallholder farmers contribute significantly to agricultural and economic development of Ghana, and in the process improve on their livelihoods and income generation.

However, the smallholder farmers in the study area are faced with a myriad of challenges including high costs of agricultural inputs and farm labour (Mangnus & van Westen, 2018), weather fluctuations, limited financial support (Bawa, 2019). Again, income realized from crop farming practices is seasonal

because of over reliance on rain fall (Baidoo et al., 2016). A risk assessment undertaken by the World Bank reported that smallholder farmers in the study area are most vulnerable as regards production and price shocks, caused by seasonal droughts and flooding, persistent increases in day temperatures resulting in climate emergency that intensifies the risks (World Bank Group, 2017). Bawa (2019) added that the challenges faced by farmers in the northern regions are not only restricted to cultivation, but also postharvest losses, storage and marketing challenges. The main cause of food insecurity among farm households in the study area is attributed to the adoption of outdated farming practices and postharvest losses (World Bank Group, 2017).

The study area falls in the savannah ecological zone where the climate is usually dry, with only one raining season that runs from May to October (Martey et al., 2020). Droughts and floods are climate-related issues also encountered annually in the study area (MoFA, 2007). Antwi-Agyei, Fraser, Dougill, Stringer and Simelton (2012) posited that the annual mean temperature in the study area is expected to rise by 0.6 degrees Celsius, 2.0 degrees Celsius, and 3.9 degrees Celsius by 2020, 2050, and 2080, respectively, while rainfall is expected to decline by 2.8 percent, 10.9 percent, and 18.6 percent respectively over the same time periods. Within this period, the study area is expected to be drier (Collier et al., 2008) hence, the single rainfall season makes irrigation an important necessity for crop production throughout the dry season (Anang & Yeboah, 2019). This is owing to increased evaporation, and further reduction of runoff and available underground water as a result of the increased temperature and decreased rainfall (Antwi-Agyei et al., 2012). The study area is also known for its poor soils (Martey et al., 2020).

Despite the challenges, the World Bank Group (2017) reported that key crops cultivated in the study area are maize, yam, millet, sorghum, rice, groundnuts, soybean, and cowpea by the majority of agricultural households (Martey et al., 2020). Maize is an important staple crop, accounting for more than half of the total cereal production, the bulk of which is produced in the northern part of the country where farming is the leading livelihood enterprise of the population (Abdulai et al., 2017). The Northern and the North East regions were the main regions of the focus of this study. Collectively, the regions were ranked fifth in average maize production in the country (three-year average, 2013–2015) (MoFA, 2017; Scheiterle & Birner, 2018). Again, MoFA-PPRSD (2018) reported that the regions were noted for the high incidence of FAW in the country.

Northern Region

The Northern Region has the largest average land holding sizes among the five regions in the northern part of Ghana (Chamberlin, 2007). In terms of population, the region has the highest population in the savannah agro-ecological zone with 1,905,628 people living in the region (Ghana Statistical Service, 2019). The region covered land area of 70,384 squared kilometres until 2018 when the North East and Savannah regions were carved out of it (Ghana Statistical Service, 2013). The land area of the region is approximately 30% of the total land area of Ghana. On the Global Positioning Scale, the Northern region is situated between latitude 8° 30'N and 10° 30' S and stretches from longitude 0° 30'E to 2°45'W (Ministry of Local Government and Rural Development, 2022).

The Northern Region shares borders with the North East Region to north, the eastern Ghana-Togo international border to the east, the Oti region to the south and the Savannah region to the west (MLGRD, 2020). The climate is relatively dry in the region, with the unimodal rainfall season between May and October recording annual rainfall figures between 750 millimetres and 1,050 millimetres (GSS, 2013). The dry periods of the year begins in November through to March/April with maximum and minimum temperatures experienced between March to April and December to January respectively (Abdulai et al., 2017). Research has indicated that temperatures recorded in the region are significantly affected by harmattan winds, which blow in the region from December to early February, hence the region experiencing temperatures between 14°C at night and 40°C during the day (GSS, 2013). The region is divided into 14 districts with Tamale as its regional capital (MLGRD, 2020). Tolon and Mion Districts in the region are two districts where data was collected for the study.

Tolon District

Tolon District is one of the districts where the study was carried out. It is estimated that the district covers land area of 1353.66 squared kilometres with a projected population of 90,027 in 2019 (GSS, 2019). Geographically the district is located between latitude 9° 15' 10" 02' North and longitude 0° 53' and 1° 25' West, and share borders with the Tamale Metropolitan Assembly to the East, North Gonja District to the West, Central Gonja District to the south and Kumbungu District to the north (MLGRD, 2020). The main vegetation in the district is generally grassland, scattered through guinea savannah wood-land

and characterised by drought-resistant woodlots such as acacia, baobab, dawadawa, mango, neem and shea nut (Konja et al., 2019).

Tolon is the district capital (MLGRD, 2020). Most of the residents (88.8%) in the district are long-term farmers who cultivate crops like cowpea, groundnuts, maize, millet, rice, sorghum, yam, etc on mostly sandy loam soils, excluding the lowland areas where alluvial deposits originate (Konja et al., 2019). It is worth noting that two main settlement patterns are evident in the district. Linear settlement, in which most communities and houses in the district are along the White Volta or the trunk road connecting Tolon and Nyankpala, and a nuclear settlement, where villages or houses are clustered (MLGRD, 2020). Farmers who participated in the study from the Tolon District were selected from Nyankpala and Kpalsogu.

Mion District

The Mion District Assembly was established on 6th February 2012 and officially inaugurated in June the same year (MLGRD, 2020). It was carved out of the Yendi Municipality because of population growth with the objective of allowing development spread to all communities in the district. It is estimated that 90,027 people live in the district in three area councils specifically; Sang, Jimle and Kpabia (Ghana Statistical Service, 2019). The population is made up of 50% males and 50% females. Mion is located on the eastern corridor of Northern Ghana between Latitude 9° 35' North and 0° 0' West and 0° 15' East and shares borders with the Yendi Municipality to the east, Tamele Metropolis, Savelugu Municipality and Nanton District to the west, Namumber North and East Gonja districts to the south, and Gushegu and Karaga districts to the north (MLGRD, 2020). Sang is the capital town of the district.

Mion District covers land area of 2714.1 square kilometres over a relatively dry, single rainfall season that starts in May and ends in October (GSS, 2013). The annual recorded rainfall figures range between 750 mm and 1050 mm (Abdulai et al., 2018, 2017). On the other hand, the dry period stretches from November through to March/April with minimum temperatures in December and January while maximum temperatures occur towards the end of the dry season (Abdulai et al., 2018). The Harmattan winds occur from December to early February which have considerable impact on day and night temperatures in the district, which range between 14⁰ C at night and 40⁰ C during the day (MLGRD, 2020). The very low humidity, lessens the influence of the daytime heat.

Mion District has large areas of grassland, interspersed with Guinea Savannah woodland and characterized by drought-resistant woodlots such as the acacia, dawadawa and Shea (MLGRD, 2020). This study was conducted in three communities in the Mion District, namely Salankpan, Klijine and Dijo. Research has shown that, the age distribution of the local people in the district demonstrates that approximately 47% of the inhabitants are less than 15 years (0-14 years) whereas nearly 49% are within the economically active age bracket (15-64 years) and about 4% being aged people above 64 years (MLGRD, 2020).

North East Region

The North East Region is one of the six newly-created regions in Ghana. Created on the 12th of February, 2019 under Constitutional Instrument (C.I) 116, the North East Region came into being through a Referendum on 27th December, 2018 in which 99.67% (205,804 out of 255,424 voters) voted YES

(MLGRD, 2020). With a population of 575,558, Nalaregu is the regional capital. The region comprises two municipalities and four district assemblies (GSS, 2019).

The region covers a land area of 9,072 square kilometres and shares boundaries to the east with Togo, the north with Upper East Region, the south with Northern Region and the west with Upper West Region to the west (MLGRD, 2020). The two municipalities and four district assemblies in the region are East Mamprusi Municipality where the regional capital is located, Bunkpurugu District, Yonyoo-Nasuan District, Mamprugu-Moagduri District, Chereponi District and West Mamprusi Municipality, which is the focus of this study (GSS, 2019).

West Mamprusi Municipality

The West Mamprusi Municipal Assembly was established in 1988 (MLGRD, 2020). In 2012 it was divided into two, resulting in the creation of the Mamprugu Moagduri District. The district was, however, upgraded to a Municipality in 2018 (MLGRD, 2020). West Mamprusi has an estimated population of 149,912, with 50.7% of the people being females the second largest population in the North East region (GSS, 2019). Walewale is the capital city of the municipality (MLGRD, 2020). The Municipality is situated within longitudes $0^{\circ}35''\text{W}$ and $1^{\circ}45''\text{W}$ and Latitudes $9^{\circ}55''\text{N}$ and $10^{\circ}35''\text{N}$, and covers a total land area of 2610.44 square kilometres (GSS, 2019). It is bordered on the East by the East Mamprusi Municipality, to the South by Savelugu Municipality, to the North by Talensi District and to the West by Mamprugu Moagduri District (GSS, 2013).

West Mamprusi has a resilient economic and functional relationships with some major communities in both Northern and Upper East regions. The Municipality has 96 communities with about 63.2% of the population living in rural settlements including a number of fishing and farming as major economic activities in the Municipality (MLGRD, 2020). The bulk of the arable land in the Municipality is found in the rural areas. Hence, most of the farmers favour staying in the rural areas for farming activities due to proximity to their farms (MLGRD, 2020). The population in the Municipality is concentrated in and around Walewale, the capital of within 10 to 15km radius including Kukua and Loagri where the study was conducted (GSS, 2013). Figure 10 is the map of the study area showing all locations.

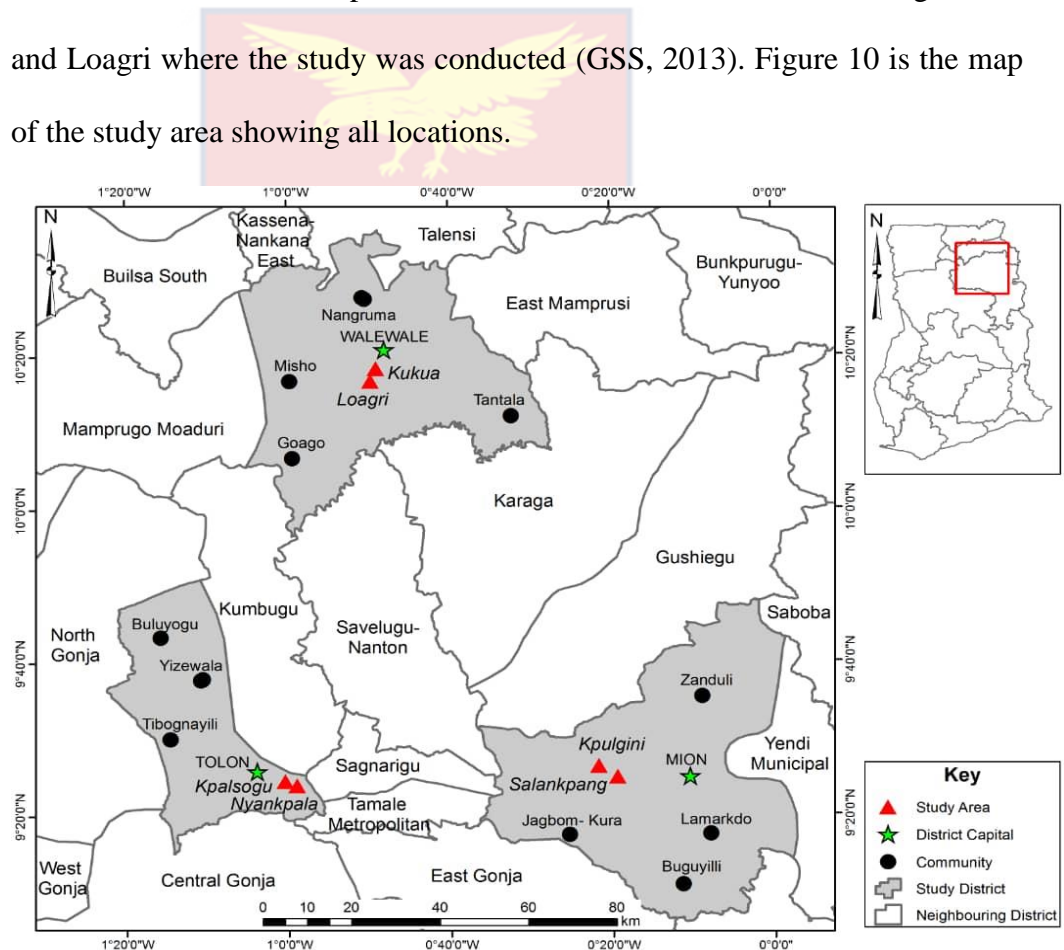


Figure 10: Map of the study area within the national and regional contexts

Source: The Department of Geography and Regional Planning, UCC (2020)

Philosophical Underpinnings of the Study

Research philosophy is the “system of belief and assumptions about the development of knowledge (Saunders, Lewis, & Thornhill, 2019, p. 124)” Saunders et al. (2019) noted that a sound research philosophical underpinning will influence the methodology, the research strategy, the procedure for data collection as well as analysis techniques. The research philosophy allowed the researcher to logically plan the research project, in a manner in which all components of research were linked together. Social scientists have developed three main philosophical paradigms, these are positivism, interpretivism and pragmatism to know what knowledge is and the methods of obtaining the knowledge (Addae & Quan-Baffour, 2015).

Scotland (2012) noted that positivist researchers study the “world” impartially and discover absolute knowledge about an objective reality. Positivists advocate that reality is fixed and objective thus, knowledge can be constructed through rigorous methodologies (Broom & Willis, 2019). On the contrary, interpretivist scholars believe knowledge should be socially created which in reality is subjective (Broom & Willis, 2019). Subjectivism combines assumptions of the arts and humanities and emphasizes social reality from creation of perceptions and ensuing actions of social actors (Saunders et al., 2019). Addae and Quan-Baffour (2015) argued that the limitations of both philosophies affect a researcher’s ability to study a social phenomenon by means of diverse lenses to gather varied information.

Hence, some scholars advocate that researchers draw on paradigmatic positions to achieve the best possible result during knowledge construction (Broom & Willis, 2019; Creswell, 2014). According to Creswell and Creswell

(2018), pragmatism as a philosophy emerges from behaviour, situations, and consequences, rather than explanatory circumstances of reality. Addae and Quan-Baffour (2015) argued that scholars need to adopt this flexible philosophical approach to study social phenomena rather than the stringent conventional approaches positivism and interpretivism have placed on scholars. Hence, the need for pragmatic approach to agricultural extension research. Saunders et al. (2019) noted that pragmatism is applicable where the study supports action and strives to reconcile subjectivism and objectivism, facts and values, accuracy and rigorous knowledge and diverse conceptualised experiences.

This study adopted the pragmatism philosophy by focusing attention on the research problem (the incidence of FAW in Northern Ghana) using both quantitative and qualitative methods to construct knowledge about the application of drone technology services for the control of FAW in Northern and North East regions of Ghana (Creswell, 2009, 2014; Creswell & Creswell, 2018). This study adopted the pragmatism anchored on the mixed methods experimental design to gain knowledge about the application of drone technology for the control of FAW in northern Ghana (Kivunja & Kuyini, 2017).

Research Design

According to Kothari (2004), research design is described as the conceptual framework for conducting research by setting up the blueprint for data collection, analysis and interpretation. It is the general approach taken by researchers to logically and coherently incorporate various study components together (VanderStoep & Johnston, 2009). A good research design ensures that

the evidence gathered in the study helps the researcher to address the research questions in a simplified manner (Neuman, 2014). Creswell (2014) posited that research design provides detailed instructions on how to carry out the procedures of the research. The mixed methods experimental design where the researcher integrates a key design into a broader to collect quantitative and qualitative data and integrated the information from an experimental trial was employed for the study (Creswell & Creswell, 2018). According to Creswell (2014) mixed methods collects quantitative and qualitative data and combines them using various designs (data collection, data analysis, and interpretation) with philosophical assumptions.

The basic principle underlying the usage of mixed methods design was to integrate qualitative and quantitative data to gain additional insight beyond what either quantitative or qualitative data alone could provide. Different scholars have used different terms to refer to this technique such as integrating, amalgamation, quantitative and qualitative methods, multimethod, mixed research, or mixed methodology, but recent publications, such as the *SAGE Handbook of Mixed Methods in the Social & Behavioural Sciences* and *SAGE's Journal of Mixed Methods Research*, tend to use the term mixed methods (Bryman, 2006; Creswell, 2014; Tashakkori & Teddlie, 2013).

Mixed methods approach arose in its current form in the late 1980s and early 1990s, based on the work of individuals from different fields such as assessment, education, management, sociology, and health sciences (Creswell & Creswell, 2018). It has gone through several stages of growth and expansion, and it is still developing, especially in terms of procedures which have been outlined by some scholars (Creswell & Plano Clark, 2018; Tashakkori &

Teddle, 2013). Mixed methods design was adopted for the study because it provided the strategy for gaining a better understanding of research problem and questions by contrasting the various points of view derived from quantitative and qualitative data and augmenting experiment (drone applied pesticides for control of FAW) by adding the perspectives of maize farmers in the process (Creswell & Creswell, 2018).

This study adopted the mixed methods experimental design to collect and analyze quantitative and qualitative data and integrated the information from an experimental trial. The design was used to add qualitative data into the drone experimental trial in order to integrate the personal experiences of the maize farmers into the research (Creswell & Creswell, 2018). The significant participation of maize farmers in many aspects of the study such as the drone trials, data collection and analysis of quantitative and qualitative data within the study is what distinguishes it as mixed methods experimental design (Creswell & Plano Clark, 2018; Tashakkori & Teddle, 2013). There are a myriad of challenges to performing mixed methods research (Bryman, 2006). Molina-Azorin (2018) argued that mixed methods study necessitates a substantial commitment of resources such as money, time and effort, and researchers must learn a wider range of skills in quantitative and qualitative research. The challenges also include the need for detailed data collection, the time-consuming nature of analyzing qualitative and quantitative data, and the researcher's knowledge of both quantitative and qualitative analysis methods (Creswell & Plano Clark, 2018; Creswell & Creswell, 2018)

Despite the challenges, Greysen, Allen, Lucas, Wang and Rosenthal (2012) studied the transitions of health care of homeless patients from hospital

to shelter in United States with mixed methods experimental approach in partnership with healthcare personnel and clients from a homeless shelter. The authors found the design very useful for gathering quantitative and qualitative data regarding changes in treatment from hospital to the shelter homes. Qualitative data was analyzed using the constant comparative approach to assess patients' perceptions on the discharge experience, and quantitative data using frequency analysis to determine factors correlated with poor outcomes from the viewpoint of patients. This study adopted the mixed methods experimental design within research priorities of controlling FAW and designed cross-sectional surveys as part of the core quantitative approach. The data collection and analysis revealed a convergent design by integrating themes and statistical results.

The repeated cross-sectional surveys were used to gather data from the maize farmers for the purpose of assessing the characteristics, opinions, attitude, behaviour and knowledge of the farmers at one point in time on four irregular occasions as part of the quantitative approach (Baltagi, 2005; Kesmodel, 2018; Steel, 2008). Repeated cross-sectional survey allowed the researcher to directly observe the phenomenon under investigation, gathered information in a limited amount of time to obtain quicker results at a lower cost (Zangirolami-Raimundo et al., 2018).

Repeated cross-sectional surveys facilitated an independent selection of maize farmers to ensure that there was no overlapping of samples between the time periods (Steel, 2008). This study used the advantages of repeated cross-sectional designs, such as the reduction of attrition and response bias, as well as the ability to maintain sample sizes to hold the sample size constant (Lebo &

Weber, 2015). The same maize farmers in the six communities were surveyed on four different occasions to collect data on awareness, knowledge and farmers' FAW control methods, perception on drone technology for pesticides application to control both on video and live application and acceptance of drone services for control of FAW (Lebo & Weber, 2015). The design enabled the variables each of the objectives to be measured on different occasions during the study (Baltagi, 2005). The design also enabled hypotheses and correlations to be tested by analyzing data from the sample to make inferences about the study population (Creswell & Creswell, 2018).

The research sought to enable agricultural extension agents and researchers act as 'innovation agents' and facilitators of multi-stakeholder innovation processes (Dugan et al., 2013; Klerkx et al., 2012; Kraaijvanger et al., 2016). Therefore the Participatory Action Research (PAR) was adopted as the second research design. Participatory action research enabled generation of knowledge that supported social change involving maize farmers' use of drone technology for control of FAW in northern Ghana (Wadsworth, 1998). The study involved the researcher and maize farmers in six communities in northern Ghana improving production of maize due to the devastating effect of FAW since it was reported in Ghana in 2016 (Macdonald, 2012). PAR combines research process with education and action to ensure learning and transformation of clients (Kidwai et al., 2017).

Central to PAR study are action and participation. Action because the study sought to make tangible, positive change to the behaviour of the maize farmers and their communities. Participation ensured the involvement of farmers in all the stages of inquiry to bring the associated change processes

(Klocker, 2015). The research is a collaboration with stakeholders involved in research experimental trials in selected communities in Salanpkang in the Mion District, Nyankpala in the Tolon District, and Kukua in the West Mamprusi Municipality setup by the Savanna Agriculture Research Institute (SARI).

PRA enabled the organization of nine Farmer Field Days (FFDs) on three different occasions for collection of data on farmers' perception on drone and knapsack pesticides application for control of FAW on the experimental plots. Three FFDs were held in Kukua, Salanpkang, and Nyankpala respectively. The first pesticides application with the drone and knapsack sprayer on the trial plots was captured in a video recording and shown to the farmers after which farmers had the opportunity to visit the experimental plots to observe the fields.

During the second instalment of three FFDs, the farmers had the opportunity to observe the field application of pesticides using the drone and knapsack sprayer from a safe perimeter defined and demarcated for observation. The final three Farmer Field Days were at harvesting of the maize from the trial fields. Farmers were permitted to enter the experimental plots and inspect the corn in the plots as well as the yield from the experimental plots. Focus group discussions and participants' observations were used during the FFDs to elicit the collective opinions of the farmers on the drone and knapsack pesticides application trials (Hall et al., 2017).

Study Population

Population in a research consists of all people who are of concern to the study (Marczyk et al., 2005). It is a group of people from which the researcher would collect the details needed to response the research questions (Kumar,

2011). The study population was all maize farmers in the Northern and North East Regions of Ghana. The target population of the study was all maize farmers registered with the Department of Agriculture in the three study districts; however, the accessible population were the maize farmers living and farming in and around the six selected communities, namely: Salankpang and Kplijine, Nyankpala and Kpalsogu and Kukua and Loagri in the Mion, Tolon and West Mamprusi Municipality respectively. The accessible population was the 300 beneficiary maize farmers who participated in the collaborative research project from the communities formed the population and sampling frame of the study. The sampling frame had 100 maize farmers in Kukuua and Loagri, 100 in Nyanpkala and Kpalsogu and 100 in Kplijine and Salankpang (Table 4).

Table 4: Population of beneficiary maize farmers in the communities

District	Communities	Beneficiary maize farmers
Tolon	Nyankpala	50
	Kpalsogu	50
Mion	Salankpang	50
	Kplijine	50
West Mamprusi	Kukua	50
	Loagri	50
Total		300

Source: Department of Agriculture of Mion, Tolon and West Mamprusi (2020)

Sampling and Sample Size for the Study

Sarantakos (2013) described sampling as the procedure for extracting samples from study populations. It helps to obtain data from a subset of the total study population such that the information collected is representative of the study population (Cohen et al., 2007). Sampling decisions are made based on the population characteristics and type of research (Creswell & Creswell, 2018;

Flick, 2018). This study was a collaborative research involving the Department of Agricultural Economics and Extensions, University of Cape Coast, the CSIR-Savannah Agricultural Research Institute (CSIR-SARI), Bayer CropScience of Paris and AcquahMeyer Drone Tech Ltd, Accra. The main aim was to examine the efficacy of synthetic chemicals for the control of Fall Armyworm FAW control using drone application. Hence, the determination of the sample depended on the objectives of the collaborative research.

The study therefore adopted purposive and multi-phase sampling techniques to select the sample of respondents for the study (Neuman, 2014; Sarantakos, 2013). As part of the collaborative research, there was purposive selection of experimental plots by CSIR-SARI in Salankpang in the Mion District on the eastern part of the Northern Region, Nyankpala in the Tolon District of the western part of the region and Kukua in the West Mamprusi Municipality of the North East Region. The purposive selection of the experimental plots was based on different vegetation and climatic conditions in the three locations (CTA, 2019a). Also, the selected communities of the experimental plots are in districts (Mion, Tolon and West Mamprusi) and regions (Northern and North East) which were regarded as epicentres of the FAW infestation the Northern part of Ghana. Another criterion was the centrality of the locations of the experimental plots which were within 5-10 Kilometres radius from the surrounding communities in the epicentres. Based on 5-10 Km criterion, two communities each were selected for the study. The communities were Salankpang and Kplijine, Nyankpala and Kpalsogu, and Kukua and Loagri respectively.

The multi-phase sampling techniques were used for the selection of respondents for the study. The multi-phase sampling technique was used to facilitate initial data collection from the sample before another sample was drawn from the same sample (Sarantakos, 2013). Two phases of the multi-phase sampling was carried out in this study. Phase one involved the random selection of three hundred (300) maize farmers from the six communities in the three districts maize farmers with the Department of Agriculture in the selected communities. During this phase of the sampling process, sampling frame of the registered maize farmers in the six communities from the three Department of Agriculture in the districts were collated and used for the study. Using the lottery method of sampling, 300 maize farmers were selected for the study, 50 farmers from each of the six selected communities (Kothari, 2004; Neuman, 2014; Sarantakos, 2013; VanderStoep & Johnston, 2009).

The three hundred (300) maize farmers participated in a socio-economic survey on awareness, knowledge and FAW management methods which which formed the sampling frame for the study. The second phase of the sampling process involved the disproportionate random selection of 150 maize farmers (50 farmers in each district and 25 farmers from each community) from the previously selected 300 farmers to participate in the experimental trials where drone and knapsack application of pesticide was done to control FAW on the experimental plots. The purpose of stratifying was to ensure that equal number of farmers were selected from the three districts to participate in the experimental demonstrations (Kline, 2005).

The list of the 300 farmers was typed in to spread sheet (Microsoft Excel 2016) software with names, sex, age, years of farming experience as well

as their respective farm sizes and yields from the previous planting season. The Microsoft Excel Spread Sheet was used to draw 150 maize farmers from the sampling frame of 300 maize farmers to participate in this study (Kenyon, 2010; Menard, 2005; Tubaishat et al., 2016). Therefore, the 150 maize farmers represented the final sample size for the study.

The question about the appropriate sample size to use in social science research has attracted attention from scholars and researchers from different schools of thought (Sarantakos, 2013). Pallant (2016) posited that the issue of concern with the sample size of a study is generalisability (p. 123). Gravetter and Wallnau (2005) also argued that bigger sample reduces the question of sampling error which is inversely proportional to sample size. Pallant (2016) noted that a study with a small sample size may obtain results that cannot be generalised to the population. Different scholars have provided different guidelines regarding the appropriate number of respondents for different statistical analysis in the research process to improve the generalisability of research (Sarantakos, 2013).

Stevens (1996) posited that “for social science research about 15 subjects per predictor are needed for a reliable regression equation (p. 72).” Tabachnick and Fidell (2013) also recommended a formula for estimating the required sample size for regression analysis considering the number of predictors: $n \geq 50 + 8m$ (where n = sample size, m = number of predictors) and $n \geq 104 + m$ for analysing individual predictors. Therefore, the 150 maize farmers as the subjects of the study were appropriate for computing multiple OLS regression in this study. Tabachnick and Fidell (2013) and Pallant (2016) recommended that a sample size of 150 or more and a ratio of at least five cases

for each variables was needed for Principal Component Analysis (16 variables) and Structural Equation Modelling (14 variables). Therefore, the sample size of 150 respondents used in this study was appropriate for computing Principal Components Analysis and Structural Equation Modelling to estimate the underlying components and relationships between the variables of the study.

Hair Jr, Hult, Ringle and Sarstedt (2017) also indicated that as a rule of thumb for Partial Least Squares Structural Equation Modelling (PLS-SEM), the sample size of the study should be 10 times the numbers of arrowheads pointing at any variables in the outer model. The number of arrowheads pointing to the variables in the outer path model used in this study was eleven, hence, the minimum samples size required for this study based on the 10 times criteria would be 110 respondents. Therefore, the 150 maize farmers used for this study was appropriate for computing PLS-SEM to examine the desire, willingness of maize farmers to adopt drone spraying services for Fall Armyworm control.

The unit of analysis of the study was maize farmers while the unit of observation was the experimental fields where drone and knapsack for pesticides applications for FAW control set up by CSIR-SARI. The 150 randomly sampled maize farmers from a cohort of 300 farmers selected during socio-economic study. The 150 maize farmers encompassed of 25 farmers from each of the six selected communities in the three districts where the trial fields were set-up. Same farmers were surveyed at the various stages of the research process. The breakdown of the actual sample size from each of the six communities in the study is presented in Table (5).

Table 5: List of Communities and Sample Sizes

District	Communities	Socio-economic study	Sample size for experiments
Tolon	Nyankpala	50	25
	Kpalsogu	50	25
Mion	Salankpang	50	25
	Kplijine	50	25
West Mamprusi	Kukua	50	25
	Loagri	50	25
	Total	300	150

Source: Department of Agriculture of Mion, Tolon and West Mamprusi (2020)

Instrumentation

Two types of instruments were used for the study, Structured Interview Schedule and Focus Group Discussion Guide. The structured interview schedule was used to collect quantitative data while the focus group discussion guide was used to elicit qualitative data for the study (VanderStoep & Johnston, 2009). The structured interview schedule was adopted for the study because the respondents could not read and write and had to be interviewed by trained enumerators to collect data in the spoken languages in the area (Dagbani and Mampruli) (Creswell, 2014; Sarantakos, 2013; VanderStoep & Johnston, 2009).

The structured interview schedule was sub-divided into five main parts aligned with the study objectives. Part one of the structured interview schedule was used to collect data on the socio-demographic and farm related characteristics of the respondents (Appendix C). The socio-demographic and farm-related characteristics collected using the instrument included but not limited to; sex of respondents operationalized as male and female, age at last birthday, level of education attained by the respondents such as primary, Junior High, Senior High and Tertiary, marital status that is married, single, divorced or widowed, number of years of maize farming experience. The rest are farm

size cultivated by farmers, yield of maize harvested by the farmers, and revenue from maize sales.

The second part of the structured interview schedule was developed to elicit data on awareness of farmers on the use of drone technology in agriculture which was objective one of the study (Appendix C). Awareness was operationalized as whether the farmers have seen or heard of the use drone technology in agriculture. Part two of the structured interview schedule also measured the level of awareness of farmers, the source of awareness and participation of farmers in drone applied agricultural activities. The variables were measured on the nominal scale.

The third part of the structured interview schedule collected data for objective two of the study which sought to collect data on the perception of the farmers on the benefits of drone technology for the control of FAW. Sixteen perceived benefits of technological innovations were identified and used in the study. Variables such as: 'drone technology saves time', 'makes pesticides application easier', 'limits chemical wastage during application' and 'less volume of chemical needed when using drones application' were used for the study. A ten point visual analogue scale of 1 = 'Very low benefit' to 10 = 'Very high benefit' was adopted to measure the perception of the farmers on the benefits of drone spraying services for Fall Armyworm control (Krabbe, 2017).

Objective three of the study which compared the perception of the farmers on the costs and benefits of using drone and knapsack to control FAW was positioned in part four of the structured interview schedule (Appendix C). Items such as: 'efficiency of equipment', 'performance in FAW control', 'ease of use', 'amount of capital needed to acquire the equipment', 'flexibility of

manipulation' and 'cost of maintenance', were used to measure the economic costs and benefits of using drone technology or knapsack sprayer for control of FAW. A ten point visual analogue scale of 1 = 'Very low' to 10 = 'Very high' was used to measure the perception of farmers on the costs and benefits of drone technology, and knapsack sprayer for control of FAW (Krabbe, 2017).

Objective four of the study meant to assess factors influencing farmers' perception to enable them to accept drone technology for control of FAW was sited in part five of the structured interview schedule (Appendix C). The study adopted and modified the variables of technology acceptance model by Venkatesh and Bala (2008). Perceived acceptance was measured in terms of perceived usefulness (PU), perceived ease of use (PEOU), computer self-efficacy (CSE), perceived external control (PEC), computer playfulness (CPLAY), computer anxiety (CANX) and perceived enjoyment (ENJ). The rest were subjective norm (SN), voluntariness (VOL), image (IMG), job relevance (REL), output quality (OUT), result demonstrability (RES) and behavioural intention (BI). A ten point visual analogue scale of 1 = 'Very low' to 10 = 'Very high' was used to measure the perception of farmers on the factors which enabled them to accept drone technology for control of FAW (Krabbe, 2017).

A focus group discussion guide was used based on the design of the study (Appendix D). The FGD guide was employed to collect qualitative data to complement the quantitative data collected using the structured interview schedule (Krueger, 2002; Michaelson, 2017). The FGD guide was used to obtain data on the awareness of farmers on the application of drone technology in agriculture, the perception of the benefits of drone spraying services for Fall Armyworm control and costs and benefits of using drone technology and

knapsack sprayer for control of FAW. The qualitative data helped to gain a deeper understanding of the use of drone spraying services for FAW control (Duke, 2005; Nyumba et al., 2018).

The FGD was adopted because the technique encouraged group interactions among the maize farmers during the data collection (Carson et al., 2011). The instrument was made up of open-ended questions which elicited qualitative data aligned to the objectives of the study (Krueger, 2002; Michaelson, 2017; Nyumba et al., 2018). The FGD guide was divided into three main parts: Part one was used to obtain data on the awareness of the farmers on the application of drone technology in agriculture, Part two measured farmers' perception on the benefits of drone spraying service for Fall Armyworm control, whereas the third part compared the perceptions of farmers on the use of drone sprayer and knapsack sprayer for Fall Armyworm control.

Pre-Testing of the Instruments

The instruments were pre-tested on thirty (30) maize farmers who were not part of the 150 selected for the experimental trials. These were farmers who were not selected as part of those in the drone experimental exercise. Pre-testing provided the opportunity to clarify misleading questions, problems, grammatical and typo-graphical errors on the instruments for improvement (Kline, 2005). The exercise was carried out between 21st and 23rd October, 2020 in the study area where some items on the instruments were corrected, modified, clarified and in some cases deleted. For example, item one on the perception of the uses of drones which read 'video of use of oil and gas exploration' was modified to read 'used for taking videos during oil and gas exploration', again item number seven on the same scale read 'used to monitor security of the

people’ was changed to read ‘used by the security agencies to monitor security in the community’. Furthermore, item eight was also modified to read ‘used for land surveying and plot measuring’.

Also, the structured interview schedule for data collection omitted the number of bags of maize the farmers harvested from their farms in the 2019 cropping season. The question on the yield of maize harvested by the farmers was incorporated in part five of the instrument. The pre-test also aided to adjust the various sub-scales of the visual analogue scales used. The pre-testing respondents indicated that some questions were similar, hence, affected their understanding and comprehension of the questions. These items were either merged or removed from the subscales. The issues and feedback raised during the pre-test were incorporated into the final instruments used for the study (VanderStoep & Johnston, 2009). Pre-testing helped to improve the suitability, validity and reliability of the structured interview schedules (Sarantakos, 2013). The pre-testing was part of the exercise to ensure the validity and reliability of the instrument. The training of the enumerators who were used for the study was done as part of the pre-testing exercise. This also added to the processes of ensuring that the instruments were valid and reliable.

Validity of the Instrument

Validity is the degree to which theories, inferences or measurements are well established and come to an agreement accurately in the real world. It is “an overall assessment of the degree to which evidence and theory support the interpretation of the scores entailed by the proposed instrument” (Krabbe, 2017, p. 133). In general terms, an instrument is seen as valid when it obtains relevant, accurate and precise data for a study (Sarantakos, 2013). The study used face,

content and construct validity to ensure that the instrument measured what it was supposed to measure (Sarantakos, 2013; VanderStoep & Johnston, 2009). The face validity was ensured by the maize farmers, enumerators, extension agents, the candidate and other graduate students at the Department of Agricultural Economics and Extension by reviewing the items on the instrument (Krabbe, 2017). This was done by ensuring that items on the instrument were aligned with the objectives of the study.

The content and construct validity involved ensuring that the instrument empirically and theoretically measured what it was intended to measure it was certified by experts at the Department of Agricultural Economics and Extension, University of Cape Coast (Krabbe, 2017; Sarantakos, 2013; VanderStoep & Johnston, 2009). The supervisors of the study at the Department of Agricultural Economics and Extension ensured the content and construct validity of the instrument. They considered the objectives and the variables meant to be measured by each objective so that all the possible dimensions of the use of drone technology for the control of FAW in Northern Ghana was covered (Pallant, 2016; Sarantakos, 2013).

Reliability of the Instrument

The reliability of an instrument shows how free it is from random error (Pallant, 2016). It is also the extent to which the instrument yields consistent, reproducible estimates of what is assumed to be measuring (Krabbe, 2017). A reliable instrument is also internally consistent and ensures that items (Likert and dichotomus) measure the same underlying attributes (Pallant, 2016). Again, a reliable instrument shows how stable it is especially the similarity between the raters (Krabbe, 2017). Sarantakos (2013) suggested ways to ensure the

reliability of instruments. They are test-retest reliability, split-half reliability, alternative form reliability and internal consistency reliability.

The study adopted the internal consistency approach to compute the Cronbach's alpha of the visual analogue items (Gravetter & Wallnau, 2005; Krabbe, 2017; Sarantakos, 2013) and Kuder-Richardson 20 (KR-20) coefficient dichotomous items (Kline, 2005; Pett et al., 2003) to assess the extent to which the items were reliable. The data on the dichotomous and continuous subscales from the pre-test were entered into IBM SPSS version 25.0 and computed Kuder-Richardson and Cronbach's alpha coefficients to evaluate the internal consistency of subscales (Kline, 2005; Pallant, 2016; Pett et al., 2003).

Table (6) presents the Kuder-Richardson coefficients (KR-20) of the dichotomous subscales used for the study. The results revealed that the coefficient of the perception of the uses of drone was 0.76 while the parts of the spraying drone was 0.74 respectively. The outcome of the Kuder-Richardson coefficients (KR-20) indicated that the dichotomous items used for the study was reliable with high internal consistency. This is because Kuder-Richardson coefficient (KR-20) of 0.70 or higher are regarded as reliable (Nunnally, 1978; Pett et al., 2003).

Table 6: Reliability Co-efficients of dichotomous subscales

Subscales	Number of items	Kuder-Richardson coefficient
Perception on use of drone	8	0.76
Perception on the parts of the spraying drone	5	0.74

Source: Pre-Test Data (2020) n = 30.

The Cronbach's alpha coefficients of the visual analogue subscales used in the study are presented in Table (7). The results indicated that behavioural intention (BI) with three items had the lowest Cronbach's alpha coefficient of 0.70 while perceived enjoyment (ENJ) also with three items had the highest coefficient of 0.95. The rest of the subscale items were between the coefficients 0.70 and 0.95. The results of Cronbach's alpha coefficient indicated that the instruments used for the study were reliable with high internal consistencies. This was due to the fact that coefficient alpha of 0.70 or better are regarded as reliable (Pallant, 2016; Reynaldo & Santos, 1999).

Table 7: Reliability Co-efficients of the visual analogue subscales

Subscales	Number of items	Cronbach's Alpha
Perceived enjoyment (ENJ)	3	0.95
Voluntariness (VOL)	3	0.92
Computer self-efficacy (CSE)	3	0.9
Job relevance (REL)	3	0.89
Attitude towards use (ATT)	5	0.89
Computer playfulness (CPLAY)	4	0.88
Perceived ease of use (PEOU)	5	0.87
Output quality (OUT)	3	0.86
Benefits of drone	16	0.85
Perceived usefulness (PU)	5	0.85
Perceived external control (PEC)	7	0.85
Subjective norm (SN)	4	0.84
Cost and Benefits of drone	26	0.82
Result demonstrability (RES)	4	0.82
Image (IMG)	3	0.81
Computer Anxiety (CANX)	4	0.79
Cost and Benefits of knapsack	26	0.78
Behavioural intension (BI)	3	0.70

Source: Pre-Test Data, Asante (2020) n = 30

Data Collection Procedure

The study employed the face-to-face interviews and focus group discussions as the data collection methods. To facilitate data collection for the study, the agriculture departments in the designated districts were contacted, by introducing the study to them. The contacts were made to describe the study's purpose and to solicit help with field data gathering. With the support of the Agricultural Extension Agents, farmers in the pre-selected communities were contacted to participate in the research. The objective of the study was explained to the participants, and they were promised that their responses would be kept anonymous and confidential. The eight trained enumerators and interpreters assisted with data collection by translating the meaning of the questions on the instrument into local languages (Dagbani and Mampruli) the respondents while recording the responses.

The validated and pre-tested structured interview schedule was used for face-to-face interviews by trained enumerators to collect quantitative data based on the objectives of the study. Data on farmers and farm-related characteristics such as: sex of farmers, age at last birthday, farming experience, type and level of education, marital status, farm size of maize cultivated, yield of maize, and revenue from maize sales were collected (Appendix B). Data on the awareness of farmers on the use of drone technology for agriculture in was measured to satisfy objective one of the study. For objective, 16 items were used to examine maize farmers' opinions of benefits of drone spraying services for Fall Armyworm control.

To compare the perceived costs and benefits of drone technology against the use of knapsack sprayer for control of FAW, 26 economic cost and benefits

items were measured as the objective three of the study. Objective four was measured using 13 variables of TAM 3 (Venkatesh & Bala, 2008). The TAM 3 was adopted and modified based on the objective of this study (Appendix C). Qualitative data was also collected using focus group discussion during the farmer field days with the help of focus group discussion guide (Appendix D). Each of the three experimental plots hosted three focus group discussions.

The first was after the farmer watched the video on drone and knapsack pesticides application. The second set of FGDs were held during live drone and knapsack application of pesticides then the final installment of the fields were held when the crops were ready to be harvested. In total nine FGDs were conducted during this study. The different response rates of farmers during the entire data collections is presented in Table (8). The response rates show that 145 out 150 (96.67% response rate) farmers participated in the field days where the video of pesticides applications were shown. The results also show that 105 (70% response rate) and 150 (100% response rate) farmers participated in the second and third data collections respectively. According to Baruch and Holtom (2008), the minimum response for a survey using primary data from individuals is approximately 53% or higher, indicating that the response rate of the maize farmers during the second pesticides application was valid. Data collection from the farmers was conducted from 9th November, 2020 to 18th December, 2020.

Table 8: List of Communities and Actual Samples Sizes after Data Collection

District	Selected Communities	Video Applications	Live Applications	Harvesting of Fields
Tolon	Nyankpala	24	24	25
	Kpalsogu	24	18	25
	Salankpang	24	19	25
Mion	Kplijine	25	18	25
	Kukua	25	10	25
West Mamprusi	Loagri	23	16	25
	Total	145	105	150

Source: Field data, Asante (2020)

Data Processing

The quantitative data collected from the field was organized and cleaned to ensure that responses were consistent with the questions asked by the instruments. Some responses such as farm size and yield of maize which were measured in acres and number of bags were also modified into hectares and metric tonnes per hectare respectively. The data was entered into IBM SPSS version 25.0 after the data template has been created in the software programme based on the instrument used in the study. Descriptives such as frequencies, percentages and central tendencies such means and standard deviation were computed to evaluate errors and possible outliers during data entry. The IBM SPSS version 25.0 and Smart PLS software version 3.3.2 (Ringle et al., 2015) were used as data analysis tools to generate the results based on the objectives of the study. All hypotheses were also computed at 0.05 alpha level.

Quantitative Data Analysis

Descriptive statistics such as frequencies, percentages, means and standard deviation and cross-tabulation were computed to describe the farmers

and farm related characteristics of the respondents of the study. Objective one which sought to examine awareness of farmers of the use of drone technology for agriculture was analysed using frequencies, percentages and cross-tabulation to describe the awareness of maize farmers of the use of drone technology in agriculture (Muijs, 2004; Pallant, 2016).

Objective two of the study which sought to examine the perception of farmers of the benefits of drone spraying services for Fall Armyworm control in the study area was analysed using means, standard deviations, principal components analysis (PCA) and multivariate analysis of variance (MANOVA) (Gravetter & Wallnau, 2005; Krabbe, 2017; Pallant, 2016). The goal of using principal component analysis was to decompose the data set on the benefits of the technology for control of FAW with correlated variables into a new set of uncorrelated factors (Krabbe, 2017). Principal component analysis was used to produce an empirical summary of the data set on the perception of maize farmers on the benefits of using drone technology for the control of FAW in the study area (Pallant, 2016). MANOVA was used to examine the difference of the linear combination of the factors among the farmers in the three districts.

The study would compare the perceived costs and benefits of drone technology against the use of Knapsack sprayer for the control of FAW in the study area from the perspective of farmers. Objective three was analysed using means, standard deviations and paired samples t-test to compare the perceived costs and benefits of using drone technology and knapsack sprayer for control of FAW (Leech et al., 2005; Pallant, 2016; Tabachnick & Fidell, 2013).

To find out whether farmers are willing to use drone technology to control their FAW, structural equation modelling (SEM) was used to model the

desire or tendency of the farmers to adopt the usage of drone spraying services for Fall Armyworm control in the study area (Krabbe, 2017; Tabachnick & Fidell, 2013). Structural Equation Modeling, a second generation multivariate analytical method was used to simultaneously test and estimate the complex hypothetical causal relationships among the TAM 3 variables used to model the adopt drone for pesticides application for the control of FAW in the study area (Astrachan et al., 2014). Researchers apply two main types of SEM in different field of study: covariance-based SEM (CB-SEM) and partial least squares SEM (PLS-SEM) also called PLS path modeling (Hair, Hult, Ringle, & Sarstedt, 2017). CB-SEM is basically used to confirm or reject theories while PLS-SEM is utilized in exploratory research to develop theories (Hair, Sarstedt, Pieper, & Ringle, 2012).

Joreskog and Wold (1982) posited that, CB-SEM and PLS-SEM are different but complementary statistical techniques for research situation where the advantages of the one technique are the disadvantages of the other and vice versa. Scholars believe that, PLS-SEM is applied when the research objective is motivated by prediction and explaining the variance of key target constructs by different explanatory constructs, the sample size is relatively small and/or the available data is non-normal; and in situation when CB-SEM provides no, or at best questionable results (Hair et al., 2011; Hair et al., 2012; Hair et al., 2019). PLS-SEM was adopted for this study for testing the hypothesis because analytical technique has few assumptions about data distribution (Hair et al., 2011).

The PLS-SEM was used because it does not require assumptions of normality for data set as it employs bootstrapping for estimating parameters

(Henseler et al., 2014). The assumption of normality was therefore not assessed. PLS-SEM was also considered better for testing constructs with fewer indicator variables (Shukla & Sharma, 2018). Subsequently, as the constructs were measured using three to five indicator variables, PLS-SEM seems to be relevant for conducting the analysis. Again, the TAM 3 indicator constructs used in the study were reflective in nature and predefined (Coltman et al., 2008; Shukla & Sharma, 2018).

Furthermore, PLS-SEM was adopted for this study because it is regarded as soft-modeling technique as it has delivered accurate results with less assumptions. The PLS-SEM method was used for data analysis over covariance-based structural modeling (CB-SEM) as the objective of this study was to identify key driver constructs not theory testing or comparison (Hair et al., 2011). Finally, the software SmartPLS website has clarified the use of PLS-SEM over CB-SEM using the TAM model (Shukla & Sharma, 2018). The SmartPLS software version 3.3.2 was used for computing the PLS-SEM (Ringle et al., 2015).

Qualitative Data Analysis

Qualitative data from the group discussions were analysed manually in the following steps:

1. organizing and preparing for data analysis by transcribing group discussions and field notes and rearranging information based on the research questions.
2. reading through the data to gain a general sense of information provided by the farmers for better understanding.

3. coding by organizing the data and writing words to represent categories or themes.
4. utilizing the coding process to create descriptions of the themes for analysis.
5. representing the themes by qualitative narrative passages to convey the results of the analysis (Creswel & Creswell, 2018, pp. 260-262).

Theoretical Specification of Structural Equation Model (SEM): The PLS-SEM Approach

The modified Extended Technology Acceptance Model 3 by Venkatesh and Bala (2008) formed the theoretical basis of this study. The goal of using TAM 3 in this present study was to explain the effect of the perceived usefulness of drone technology services, its ease of use and attitude towards its use on the behavioural intention of maize farmers to use and ultimately adopt the technology for spraying pesticides for the control of FAW in selected districts in northern Ghana. Behavioural intention (BI) in this study is the intention of the maize farmer to utilize drone for pesticides application for control of FAW in the study (Venkatesh & Bala, 2008). Behavioural intention was measured using perceived usefulness (PU), perceived ease of use (PEOU) and attitude towards use (ATT), initially developed by (Davis, 1989). The model was later extended by (Venkatesh & Davis, 2000) in 2000. The novel TAM proposed by Davis (1989) sought to examine the attitude and belief of technology users that affect the intention to accept or reject new technologies. As part of the limitations of TAM developed without intrinsic motivation and user emotions in the explanation of intention to use technology in TAM (Davis, 1989), Venkatesh and Davis (2000) proposed two theoretical processes, social influence and

cognitive instrumental processes to expound the impact of the contributing factor of PU and BI referred to as TAM 2.

Subjective norms and images are components of social influence whiles PEOU, job relevance, output quality, and result demonstrability are the components of cognitive instrumental processes (Alomary & Woollard, 2015; Venkatesh & Davis, 2000). TAM 2 also demonstrated certain amount of weaknesses, therefore in a bid to make TAM more comprehensive, Venkatesh and Bala (2008) combined models suggested by Venkatesh (2000) and Venkatesh and Davis (2000) to develop a complete nomological network of technology adoption and use referred to as TAM 3. The model proposed additional constructs as determinants of the TAM construct perceived usefulness (PU), perceived ease of use (PEOU) and behavioural intention (BI).

The model combined TAM 2 with determinants PEOU, i.e. computer self-efficacy, perceptions of external control, computer anxiety, computer playfulness, perceived enjoyment and objective usability (Jaradat & Al-Mashaqba, 2014). The model has been validated in different countries (Lai, 2017) and implemented in numerous research studies (Al-gahtani, 2016; Amin et al., 2015; Fosso Wamba & Trinchera, 2014; Riskinanto et al., 2017; SevİM et al., 2017). The latent variables in TAM 3 exhibit favourable convergent validity and predictive validity when subjected to structural equation modelling (Richter et al., 2020; Shukla & Sharma, 2018; Venkatesh & Bala, 2008).

The model adopted for this study was made up of behavioural intention as the endogenous construct with PU, PEOU, attitude towards use and subjective norm as its driver exogenous constructs. The foundation model was measured using 22 reflective indicators on a 10-point visual analogue scale.

Building on the definition of perceived usefulness and related constructs, Venkatesh and Davis (2000) identified the determinants (drivers) of perceived usefulness as subject norm, image, job relevance, results demonstrability with moderating effect of output quality on job relevance. Image also plays a mediating role between PU and SN. The drivers of perceived usefulness was measured with 16 reflective indicators on a 10 point visual analogue scale. Venkatesh (2000) expanding on the definition of perceived ease of use, proposed the following drivers of computer self-efficacy, perception of external control, computer anxiety, computer playfulness and perceived enjoyment. The exogenous constructs of perceived ease of use were measured using 21 reflective indicators on a 10 point visual analogue scale.

The driver constructs of perceived usefulness and ease of use, the mediating effect of the two variables together with attitude on behavioural intention and the moderating effect of experience and voluntariness are components that make the TAM 3 model a complex model. In summary, the TAM 3 has two main conceptual/theoretical components; (1) the endogenous constructs (dependent variables) of interest namely, behavioural intention (BI), attitude towards use (ATT), perceived usefulness (PU), perceived ease of use (PEOU) and image (IMG) and (2) the exogenous variables which represent the main determining factor of the endogenous variables. Figure 4 exhibits the constructs and their correlations, which represented the structural model specification for which PLS-SEM used in this study. The structural model shows the concepts with its main elements (latent constructs) and cause-effect relationships (paths). Based on the constructs and their path relationships, the

following research hypothesis were formulated and proposed for the study (Figure 11).

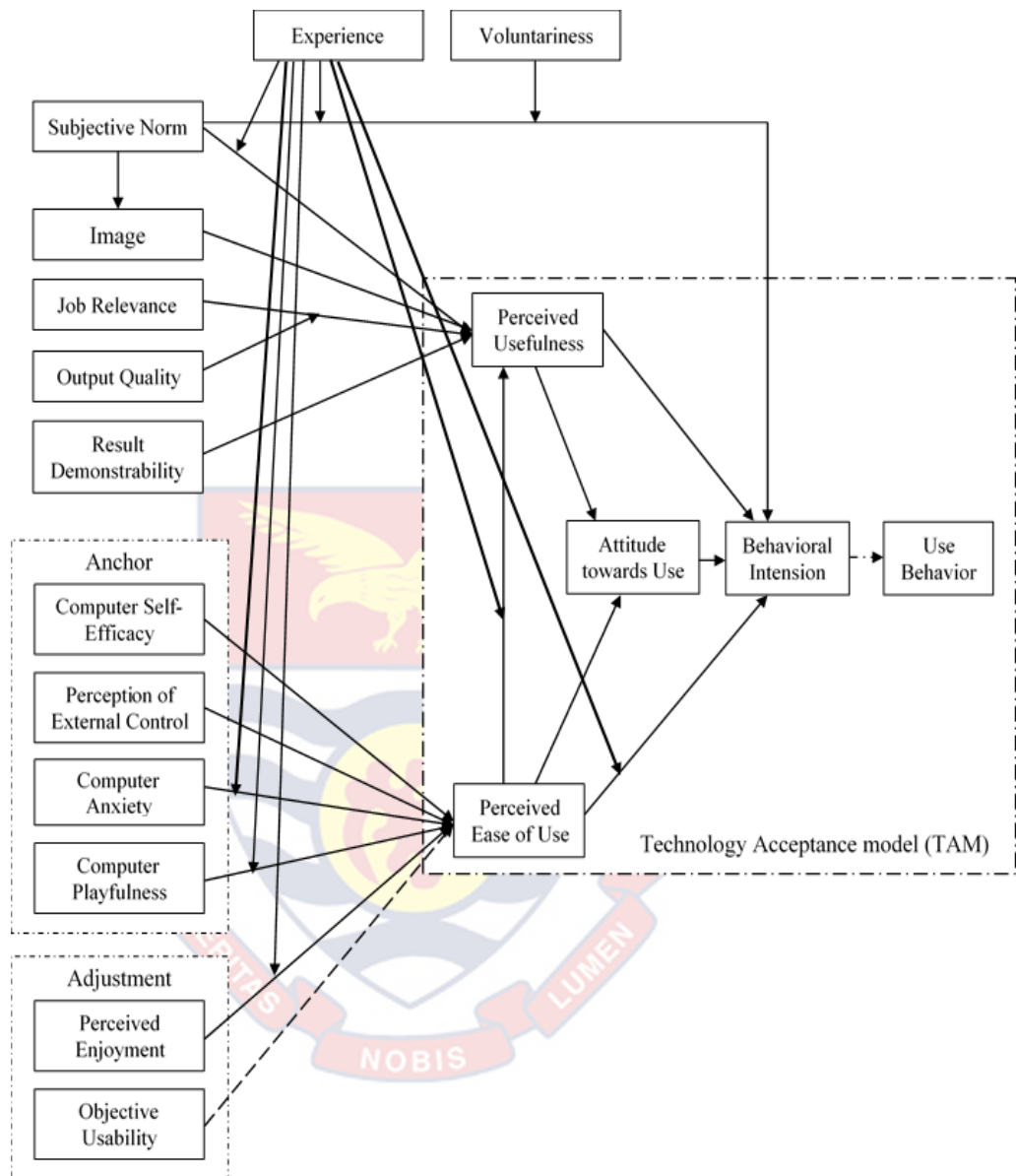


Figure 11: Research specified model for the study adopted and modified technology acceptance model (TAM3) and structural model. Dotted variables (Usage behaviour and objective usability) are omitted from the model.

Source: Venkatesh and Bala (2008)

Model Assessment

In assessing the PLS-SEM results, three key evaluation criteria were employed, namely, the assessment of the reflective measurement model,

assessment of the structural model and running of one or more robustness checks to support the stability of the model results (Hair et al., 2019). The assessment of the reflective measurement model included examining the indicator loadings, assessing internal consistency reliability, assessing convergent validity of each construct measure, and discriminant validity which is the extent to which a construct in the model is empirically distinct from other constructs in the structural model (Hair et al., 2017). Evaluating the structural model was premised on standard criteria which included the collinearity assessment, coefficient of determination (R^2), f^2 effect size blindfolding-based cross validated redundancy measure (Q^2), q^2 effect size and the statistical significance and relevance of the path coefficients (Hair et al., 2012; Hair, Hult, Ringle, & Sarstedt, 2014). The final stage was to assess the model's out-of-sample predictive power using the PLSpredict procedure to check for model robustness (Hair, Ringle, et al., 2019; Hair, Risher, et al., 2019).

Preliminary Data Screening and Examination

To estimate the Technology Acceptance Model TAM 3 in SmartPLS 3.3.2 (Ringle et al., 2015), the IBM SPSS Statistics data file was saved in a command delimited file (.csv) and imported into a new project created in the SmartPLS. The primary issues that were examined included, missing data/values, suspicious response patterns, outliers and data distribution such as skewness and Kurtosis (Hair Jr et al., 2017). The results of the assessment are presented in Table 41 (Appendix G).

Model Estimation

The path model for the TAM 3 indicators was drawn in the software to mirror the model specification of the study. The key variables in the PLS-SEM (endogenous construct), behavioural intention of maize farmers connected to its exogenous constructs [perceived ease of use (PEOU), perceived usefulness (PU), attitude towards use (ATT) and subjective norm (SN)]. PEOU and PU serving as exogenous constructs were connected to ATT as an endogenous construct. Also, perceived usefulness (PU) acting as an endogenous construct was linked with six driving exogenous constructs [perceived ease of use (PEOU), subjective norm (SN), image (IMG), job relevance (REL), and result demonstrability (RES)]. Image (IMG) acted as endogenous construct for subjective norm (SN). Finally, four anchor latent variables, computer self-efficacy (CSE), perception of external control (PEC), computer anxiety (CANX), and computer playfulness (CPLAY) and one adjustment construct, perceived enjoyment (ENJ) served as driving variable for PEOU as an endogenous construct. The impact of EXP and VOL as moderators was also estimated in the PLS-SEM.

The PLS-SEM as part of all partial regression models are estimated by the PLS-SEM algorithm's iterative procedures which were in two stages, the first was to estimate the construct score followed by estimation of the outer loading, the path coefficients and the resulting R^2 values of the endogenous latent variables (Hair et al., 2017). The PLS-SEM method used to predict the set of hypothesized relationships of Venkatesh and Bala (2008)'s extended technology acceptance model TAM 3 that maximizes the explained variance in the five dependent variables (behavioural intention (BI), attitude towards use

(ATT), perceived usefulness (PU), perceived ease of use (PEOU) and image (IMG)] (Hair et al., 2012).

Measurement Model Evaluation

The measurement model of the PLS-SEM was assessed based on construct reliability and validity and discriminant validity of the model. The indicator reliability, composite reliability, internal consistency and average variance extracted (AVE) were the criteria used to assess the construct reliability and validity of the measurement model, whereas indicator cross loading, Fornell-Larcker criterion and the Heterotriat-Monotrait ratio (HTMT) were for assessing the discriminant validity of the model (Hair, Risher, et al., 2019; Hair et al., 2017).

Indicator reliability was assessed by screening all outer loadings of the TAM 3 variables which were well above the threshold value of 0.70, a suggestion of satisfactory levels of indicator reliability (Hair et al., 2017) (Table 42, Appendix H). Composite reliability (CR) which is a measure of internal consistency reliability of the model based on Jöreskog's (1971) criteria, Cronbach's alpha and Rho_A values of the model were all over and above the threshold value of 0.70, indicating the results imply that all the reflective TAM 3 constructs used in the study had high levels of internal consistency. Higher composite reliability values indicate higher levels of reliability (Hair, Risher, et al., 2019).

Convergent validity is the extent to which a construct correlates positively to explain the variance in its indicator items was examined (Hair et

al., 2017). The indices used for evaluating the convergent validity of latent constructs were the average variance extracted (AVE) for all indicator on the construct (Hair, Risher, et al., 2019). All constructs in the model had AVE values greater than the threshold value 0.50 indicating that the latent construct explained at least 50% of the variance of its indicators (Hair et al., 2011; Hair, Risher, et al., 2019). Thus, the measures of the reflective latent constructs of TAM 3 had high levels of convergent validity (Table 42, Appendix H).

Discriminant validity is the degree to which a construct is truly different from other constructs in the model by an empirical criteria (Hair et al., 2017). The cross loadings, Fornell-Larcker criterion and the Heterotrait-Monitrait ratio (HTMT) were the three matrices used to evaluate the discriminant validity of the measurement model of the TAM 3 variables (Hair et al., 2017; Hair et al., 2011). Discriminant validity of the TAM 3 variables implied that, each of the constructs was unique and measured phenomena that were not represented by other latent constructs used in the model (Hair, Risher, et al., 2019). Indicator Cross Loadings

The indicator cross loadings was the first step in evaluating the discriminant validity of indicators in the model (Hair et al., 2017). Per the rule of thumb, an indicator's outer loading on associated latent construct should exceed its cross loadings on the other constructs in the model both on the rows and the columns. The results indicated that, indicators BI1 (0.863), BI2 (0.832) and BI3 (0.841) loaded high on its corresponding latent construct 'behavioural intention' but lowered both in the rows and the columns on the other constructs in the model. Similar cross loadings were recorded by all the other constructs in model where their indicators loaded higher on the parent constructs than the

other constructs (Table 43, Appendix I). The analysis of the cross loadings indicated that discriminant validity based on the cross loadings had been established.

The second approach for evaluating discriminant validity was the Fornell-Larcker criterion. Fornell and Larcker (1981) proposed the original metric which suggested that each latent construct's AVE should be compared to the squared inter-construct correlation (as a measure of shared variance) of that same construct and all other reflectively measured constructs in the structural model. The results of the Fornell-Larcker analysis indicated that the square root of the AVE values of the variables were higher than the inter-construct correlations in the model. Generally, the Fornell-Larcker criteria provided evidence of TAM 3 construct's discriminant validity (Table 44, Appendix J). For example, the square root of the construct behavioural intention (BI = 0.845) was higher than its inter-construct correlation with anxiety ($r = 0.665$), playfulness ($r = 0.586$), and self-efficacy ($r = 0.595$) etc.

Hair et al. (2017) argued that a recent publication has shown that, the indicator cross loadings and the Fornell-Larcker criterion were inadequate matrices for evaluating discriminant validity. Henseler, Ringle and Sarstedt (2015) demonstrated that the Fornell-Larcker criterion does not perform well, especially when the indicator loadings on a latent construct vary slightly (e.g. when all the indicator loadings are between 0.65 and 0.85). Hence as an alternative, Henseler et al. (2015) proposed the heterotrait-monotrait (HTMT) ratio of the correlations. The HTMT is defined as "the mean value of the item correlations across constructs relative to the (geometric) mean of the average

correlations for the items measuring the same construct” (Henseler et al., 2015, p. 6).

Hair et al., (2017) indicated that, discriminant validity problems arise in structural equation modelling when HTMT values are high. Henseler et al. (2015) proposed a threshold value of 0.90 for structural models with constructs that are conceptually related. In such cases, an HTMT value above 0.90 would suggest that discriminant validity is not present. However, when constructs are conceptually different, a lower, more conservative threshold value of 0.85 is suggested.

Adopting the conservative threshold values of 0.90 for related variables and 0.85 unrelated variables, discriminant validity of the latent constructs were examined which indicated that, there was discriminant validity problems in the relationship between image and job relevance (HTMT value = 0.902) and perceived usefulness and computer self-efficacy (HTMT value = 0.896) (Table 45, Appendix K). Henseler et al. (2015) recommended that when the HTMT value for relationship between two constructs is greater than the conservative threshold on 0.85, and 0.90 for conceptually similar construct, the variables are merged as one or deleted when discriminant validity cannot be established. Based on that recommendation the exogenous constructs (job relevance, computer self-efficacy) were deleted from the model (Table 45).

The structural model's collinearity was assessed to ensure that collinearity does not inflate the regression results (Hair, Risher, et al., 2019). Hair et al. (2017) suggested that variance inflation factor (VIF) values above 5 are indicative of the presence of collinearity among the exogenous constructs. Collinearity issues can also arise at lower VIF values of 3-5 (Becker et al.,

2015). Hair, Risher, et al. (2019) however posited that, the ideal VIF value should be lower or close to 3. The results of the PLS-SEM analysis presented in Table 46 (Appendix L) showed that the inner VIF values of all the exogenous constructs were found to be lower than the suggested threshold of 3 indicating the absence of collinearity among the predictive variables (Hair, Risher, et al., 2019).

As shown in Table 47 (Appendix M), the model fit index utilized for the study was the global goodness of fit index (GOF) formula by Tenenhaus, Vinzi, Chatelin and Lauro (2005) and the guidelines introduced by Wetzels, Odekerken-Schröder and van Oppen (2009) to pass judgement on the goodness of fit of the PLS-SEM model. The GOF values vary from 0 to 1, with 0.10 (small), 0.25 (medium), and 0.36 (large) indicating that the path model has global validity. A good model fit indicates that a model is lean and credible (Henseler et al., 2016). The geometric mean values of the average variance extracted (AVE values) and the average R^2 values were used to calculate the GOF. Equation (1) below proposed by Tenenhaus et al. (2005) was used to calculate the model's fitness (GOF).

$$GOF = \sqrt{\frac{AVE * R^2}{2}} \quad (1)$$

Objective five which sought to predict the socio-demographic and farm-related characteristics influencing farmers' acceptance of drone spraying services for Fall Armyworm control in the study area was analysed using OLS Stepwise multiple linear regression (Muijs, 2004; Pallant, 2016; Tabachnick & Fidell, 2013). The farmer and farm related characteristics used as independent variables were sex, age, years of farming experience, level of education,

household status, marital status, source of income, contact with extension, farm size, yield of maize, and revenue from maize sale whilst behavioural intention (BI) was used as the dependent variable.

Stepwise multiple regression statistical analysis was used to compute the best-fitting straight line for the data set (Gravetter & Wallnau, 2005; Griffith, 2010; Pallant, 2016; Rumsey, 2009). The regression line was represented in a linear equation as follows; $Y = a + \beta X$. Where ' β ' was the beta coefficient, ' a ' was the Y intercept (constant), ' X ' was the independent variables (farmer and farm related characteristics) and Y was the intention, desire or propensity of the farmers to accept drone spraying services for Fall Armyworm control. With one or more predictor variables, the equation converts; $Y = a + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \dots \beta_n X_n$. The goal of the study was to identify the exact line that provides the greatest fit and explains the variability in the intention to accept drone technology acceptance for the control of FAW in the study area. To examine the significance of the hypotheses and correlations between variables, and alpha level threshold of was used.

Twelve independent variables were used for the analysis (Table 9). Preliminary assessment indicated that there were no univariate outliers in the data set. Multivariate outliers also assessed using the Mahalonobis distance statistics in IBM SPSS. Respondent 27 recorded the highest Mahalonobis distance in the data set with a critical value of 13.077 which was less than the critical values of 32.909 at 0.001 alpha level for 12 independent variables on the Chi-Square Table (Tabachnick & Fidell, 2013). Hence, the assumption of multivariate outliers was not violated.

Table 9: Variables and their measurement included in the OLS Model

Dependent Variable	Unit of measurement	Sign	Explanation
Behavioural intention	10-Point scale		Intention or desire, propensity to accept drone spraying services for Fall Armyworm control
Independent variables			
Sex(X ₁)	Male = 1, Female = 0	+/-	Sex of respondent
Age(X ₂)	Years	+	Age at last birthday
Years of Experience(X ₃)	Years	+	Yeas of farming experience
Type of education(X ₄)	Formal = 1 In-formal = 0	+/-	Type of education attained (Formal, In-formal, No education)
Level of Education(X ₅)	Education	+	Level of formal education
Household status(X ₆)	Head = 1 Member = 0	+/-	Household status of respondent
Mrital status(X ₇)	Married = 1 Single = 0	+/-	Married and Single (Never married, Divorced, Widowed)
Contacts with Extension(X ₈)	Number of contacts	+	Number of contacts farmers have had with extension
Farm size(X ₉)	Farm Area	+	Total Land Area cultivated to maize
Yield of maize(X ₁₀)	Yield harvested	+	Yield of maize harvested in Mt/ha
Income(X ₁₁)	Income from maize	+	Income from the sale of maize in GH¢
Primary occupation(X ₁₂)	Farming = 1 Non-farming = 0	+/-	Primary Occupation of farmers

Source: Field data, Asante (2020)

Assessment of Multi-collinearity

According to Pallant (2016), multi-collinearity exists when predictor variables in an OLS regression model have a high correlation coefficient (r) of 0.9 and above. The variance inflation factors (VIFs) and tolerance of the predictor variables used in the OLS regression were examined using the collinearity diagnostic test and found to be free of multi-collinearity (Table 10). According to Tabachnick and Fidell (2013), the Variance Inflation Factor (VIF)

indicates how much multi-collinearity inflates the variance of the coefficient calculation. As a result, any predictor variable with a VIF greater than 10 indicates multi-collinearity. The VIF values of the predictor variable (Farm size = 1.00), which are all less than the threshold value (Table 10).

Table 10: Multi-collinearity Diagnostic Test Values

Independent variable	Tolerance	Variance Inflation Factor (VIF)
Farm size cultivated to maize	0.99	1.00

Source: Field data, Asante (2020)

Pallant (2016) stated that Tolerance (X_k) values of less than 0.10 suggest that the predictor variables in the model have a strong correlation with each other, implying that multi-collinearity could be a problem and that one of the strongly inter-correlating predictor variables must be removed. The predictor variable's corresponding Tolerance was higher than the cut-off point of 0.10 (Table 10). Multi-collinearity had no impact on the OLS regression model, as shown by the VIF and Tolerance values. Table 11 presents the summary of analytical tools used for the data analysis.

Table 11: Summary of Statistical Tools for Analyzing Objectives

Objectives	Statistical Tools for Analysis
One	Frequencies, percentages, means and standard deviation and cross-tabulation
Two	Means, standard deviations, principal components analysis (PCA) and MANOVA
Three	Means, standard deviations and Paired Samples t-test
Four	Partial Least Squares Structural Equation Modeling (PLS-SEM)
Five	OLS Regression

Source: Author construct, Asante (2020)

Ethical Clearance

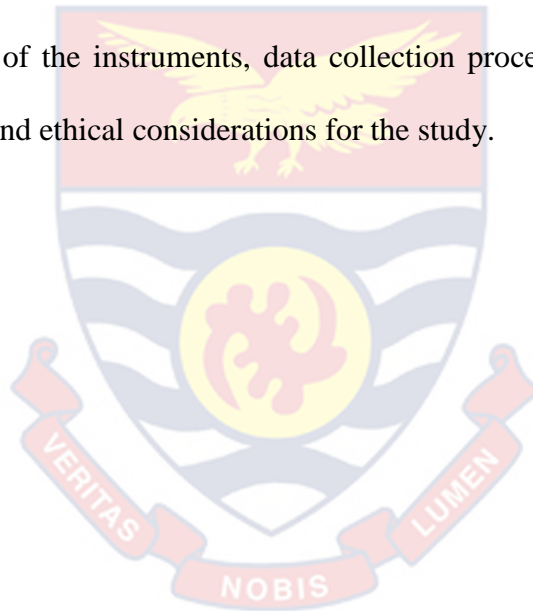
Ethical issues were considered in the study to ensure that the researcher did not violate any of the ethical codes as established by the University of Cape Coast (Sarantakos, 2013). First of all, ethical clearance for the instrument and field work was sought from the Institutional Review Board of the University. Copies of the research proposal and instruments were submitted to the Review Board for evaluation. Attached is the ethical clearance letter indicating the research was approved to be conducted in a responsible and ethically-accountable manner leading to beneficial outcome and thus was approved for data collection (Appendix B). Other ethical issues addressed during the field work were: informed consent, confidentiality of responses, possible risk and discomfort, and compensation. On the issue of informed consent, farmers who were invited to participate in this research project were informed about the objectives of the study, and the possible benefits of the results of the study to the Ministry of Food and Agriculture, and the country as a whole. They were given the opportunity to exit the project if they so wished.

All the participating farmers were assured that all information provided for the study would be treated strictly as confidential, and for educational purposes only. They were also assured that their names associated with the study would be strictly protected and not shared with any third party without their consent. Due to the nature of the feeding habit of the FAW, the field days for the application of pesticides with the drone were carried out very early in the morning which may have created discomfort for the farmers. Hence, transportation was provided for all the selected farmers to and from the demonstration sites. Farmers were also compensated for each data collection

with porridge and bread as breakfast to help mitigate the inconveniences of missing breakfast due to the field days being organised very early in the morning.

Chapter Summary

This chapter presented the methods and procedures used in carrying out the study. It looked at the description of the study area, philosophical underpinnings of the study, the research approach, research designs, population of the study and sampling techniques, procedure and sample size. Other areas covered in the chapter were instrumentation, determination of validity and reliability of the instruments, data collection procedure, data processing and analysis, and ethical considerations for the study.



CHAPTER FOUR

FARMER AND FARM-RELATED CHARACTERISTICS OF RESPONDENTS

Introduction

This chapter presents and discusses results on farmer and farm-related characteristics of respondents. The chapter is subtitled as follows: sex, age, number of years of maize farming experience, type and level of formal education, and marital status. The rest are farmers' access to agricultural extension and training, farm size cultivated to maize, yield of maize, income from maize sales, land holding arrangement, and the main sources of household income. The results from the three districts were compared due to climate and ecological variation of the locations (CTA, 2019a).

Sex Distribution of Maize Farmers

The sex distribution of the maize farmers who participated in the study is exhibited in Table 12. More than half (56%) of the farmers were males whilst the rest were females. Apart from the West Mumprusi Municipal where more females (males = 13.32%; females = 19.98%) than males participated in the study, more males participated at the Tolon (Males = 17.98%; females = 15.32%) and Mion Districts (males = 25.31%; females = 7.99%). The result mirrors the findings of many studies (Abdulai et al., 2018, 2017; Anang, 2018; Tasila Konja et al., 2019; Wongnaa & Awunyo-Vitor, 2019) that concluded that more males participate in maize production compared to females in Northern Ghana.

The finding however, differs from the gender baseline study of smallholders in the Guinea Savannah Ecological zone of Ghana by the Ghana

Feed The Future (APSP, 2014) which reported of more females (84%) than males. The high number of males reported by this study confirms the assertion of Anang (2018) and Wongnaa and Awunyo-Vitor (2019) that maize production is a male-dominated enterprise among the farmers in Northern Ghana.

Table 12: Sex distribution of Maize Farmers

Sex of farmers	Tolon District		Mion District		West Mamprusi		Overall sample	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%
Males	27	17.98	38	25.31	20	13.32	85	56.70
Females	23	15.32	12	7.99	30	19.98	65	43.30
Total	50	33.33	50	33.33	50	33.33	150	100

Source: Field data, Asante (2020). n = 150.

Age Distribution of Maize Farmers

Table 13 shows the age distribution of the respondents in the study area. More than seven out of ten of the farmers (75.90%) are between the ages of 18 and 49 years whilst the rest (24.10%) are between 50 and 79 years. The mean age is 41.40 years with standard deviation of 13.60 years. This implies the farmers who were interviewed are youthful. The future of agriculture is in the hands of rural youth. Despite this, few young people in Africa see agriculture as a viable career option (Goemans, 2014). Because farming requires more manual work than in most industries, the FAO (2018) argued that Africa's agriculture sector needs young people. While (aging) smallholder farmers in developing countries produce the majority of the world's food, these older farmers are less likely to accept the new technologies required to boost

agricultural productivity in a sustainable manner.; as a result, we must re-engage youth in agriculture (Goemans, 2014).

Table 13: Age distribution of Maize Farmers

Ages of farmers	Tolon District		Mion District		West Mamprusi		Overall sample	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%
< 30	9	6.00	9	6.00	8	5.33	26	17.30
30 – 39	14	9.33	22	14.66	8	5.33	44	29.30
40 – 49	10	6.66	14	9.33	20	13.3	44	29.30
50 – 59	7	4.66	2	1.33	8	5.33	17	11.30
>= 60	10	6.66	3	2.00	6	4.00	19	12.70
Total	50	33.33	50	33.33	50	33.33	150	100

Source: Field data, Asante (2020). n = 150. Mean age = 41.40 years, S.D = 13.60 years, Range = 18 to 79years.

Abdulai et al. (2018), Anang (2018), Konja et al. (2019) and Wongnaa and Awunyo-Vitor (2019) had reported similar mean age of farmers in communities in Northern Ghana. The age distribution of farmers is similar to the ages of farmers in the Transitional and Coastal zones of Ghana (Wongnaa & Awunyo-Vitor, 2019). As reported by Makate et al. (2017), the ages of farmers in the study area are similar to what pertains in Southern Africa. Onubuogu et al. (2014) and Mabe et al. (2018) hold the view that compared to older farmers, young farmers are more likely to accept new technologies to improve the efficiency in maize production. Abdulai et al. (2018) noted that farmers in Northern Ghana are within the youthful age bracket and regarded as economically active population as prescribed by Ghana. Hence, they are likely

to adopt the drone technology service for controlling FAW to improve the the production of maize in the study area.

Years of Farming Experience of Maize Farmers

Table 14 presents results on farmers' experience measured in number of years of farming. The results show that eight out of every ten farmers (80.70%) had been planting maize between 10 and 55 years. Only few (19.30%) had cultivated maize for less than 10 years. On the average, the farmers had cultivated maize for almost 19 years (Meant = 18.70 years, standard deviation = 11.91) but their farming experience is highly varried. Coincidentally, Bempomaa and Acquah (2014), and Wongnaa and Awunyo-Vitor (2019) reported similar mean age of farming experience of 18 years for farmers in Northern Ghana.

Table 14: Years of Farming Experience of Maize Farmers

Years of Exp.	Tolon District		Mion District		West Mamprusi		Overall sample	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%
< 10	11	7.33	9	6.00	9	6.00	29	19.30
10 – 19	18	12.00	30	20.00	14	9.33	62	41.30
20 – 29	11	7.33	8	5.33	16	10.66	35	23.30
30 – 39	5	3.33	1	0.66	6	4.00	12	8.00
>= 40	5	3.33	2	1.33	5	3.33	12	8.00
Total	50	33.33	50	33.33	50	33.33	150	100

Source: Field data, Asante (2020). n = 150. Mean experience = 18.70 years, S.D = 11.91 years, Range = 1 to 55years.

The findings, however, differ from the results of Abdulai et al (2017), Abdulai et al. (2018) and Tasila Konja et al. (2019) reported less number of years of farming experience by farmers. The farmers interviewed were likely to have enhanced knowledge to influence their decision to adopt the drone technology services for control of FAW due to their appreciable number of years of farming experience (Esiobu et al., 2014; Onubuogu et al., 2014). Wongnaa and Awunyo-Vitor (2019) posited that farmers with long years of farming experience are likely to have higher yields since they have the required experience to predict the appropriate agronomic activities for efficient production of maize.

Type and Level of Education of Maize Farmers

The distribution of level of education exhibited in Table 15 shows that seven out of every ten maize farmers (76%) have had no formal education. The results mirror the findings of Wongnaa and Awunyo-Vitor (2019) on farmers in the Guinea Savannah zone of Ghana that concluded that close to seven out of every ten farmers sampled had no formal education. More than three quarters (80.50%) of the farmers with formal education had primary (27.80%), Junior Secondary/High School (33.30%) and Senior Secondary/High School (19.40%) education whilst about a fifth (19.40%) had had Tertiary education. The average number of years spent by the respondents in school was 9.39 years (standard deviation = 3.77 years).

The results contrast the findings of Bempomaa and Acquah (2014), Anang (2018) and Tasila Konja et al. (2019) who respectively reported 7 years, 5.76 years and 3.93 years the farmers spent in school. The study confirms the assertion of Abdulai et al. (2018, 2017) that farmers in the Northern belt of

Ghana have a relatively low level of formal education. According to Esiobu et al. (2014), farmers exposed to higher level of education have an additional benefit with respect to achieving yield in maize production due to the ability to comprehend agricultural information in English Language. Hence, the low level of education of farmers is likely to affect the yield of maize in the study area.

Table 15: Type and Level of Education

Type of Education	Tolon District		Mion District		West Mamprusi		Overall sample	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%
No Edu.	38	25.33	42	28.00	34	22.66	114	76.00
Formal	12	8.00	8	5.33	16	10.66	36	24.00
Total	50	33.33	50	33.33	50	33.33	150	100
Level of Formal Education								
Primary	1	0.66	0	0.00	9	6.00	10	27.80
JSS/JHS	6	4.00	3	2.00	3	2.00	12	33.30
SSS/SHS	0	0.00	5	3.33	2	1.33	7	19.40
Tertiary	5	3.33	0	0.00	2	1.33	7	19.40
Total	12	8.00	8	5.33	16	10.66	36	100

Source: Field data, Asante (2020). n = 150. Mean years spent in school = 9.39 years, S.D = 3.77 years Range = 4 and 20 years.

Marital status of Maize Farmers

Table 16 presents the results on the marital status of the maize farmers who participated in the study. Nine out of every ten of the farmers (93.30%) are married whilst only a few (6.70%) were single. The number of married farmers is evenly distributed across all the three districts where the research was carried out. The results are consistent with the findings of Tasila Konja et al. (2019)

who revealed that close to eight out of every ten of the farmers sampled in Northern Ghana were married. Married farmers tend to have an advantage over land and labour resources. According to Onubuogu et al. (2014) and Mabe et al. (2018), married maize farmers have access to enhanced land tenure systems and large family resource of labour for maize production

Table 16: Marital status of Maize Farmers

Marital Status	Tolon District		Mion District		West Mamprusi		Overall sample	
	Freq.	%	Freq.	%	Freq.	%	Total	%
Married	46	30.66	46	30.66	48	32.00	140	93.30
Single	4	9.77	4	9.77	2	1.33	10	6.70
Total	50	33.33	50	33.33	50	33.33	150	100

Source: Field data, Asante (2020). n = 150.

Number of Extension Training Sessions Attended by Maize Farmers since 2018

The results presented in Table 17 show that the most (87.33%) of the farmers received between 3 to 9 extension visits and training sessions in the 2018 farming season. The mean number of extension visits and training sessions received by farmers in the study area was 7.23 with standard deviation of 4.85 but ranged between 3 and 30. The results of the study are consistent with the findings of Tasila Konja et al. (2019) who reported that majority (64%) of farmers received extension visits seasonally. Six out of every ten farmers received one or more visits and training services every planting season. It is worth noting that all the farmers received extension visits and training sessions in 2018 cropping season. This is contrary to the position of Tasila Konja et al.

(2019) who reported that, 36% of farmers did not receive extension visits or training.

Table 17: Number of Extension Trainings Attended by Maize Farmers since 2018

No. of Ext. Trainings	Tolon District		Mion District		West Mamprusi		Overall sample	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%
< 10	47	31.33	35	23.33	49	32.66	131	87.33
10 – 19	3	2.00	7	4.66	1	0.66	11	7.33
>20	0	0.00	8	5.33	0	0.00	8	5.33
Total	50	33.33	50	33.33	50	33.33	150	100

Source: Field data, Asante (2020). n = 150. Mean of Ext. Trainings = 7.23, S.D = 4.85, Range = 3 to 30 visits.

Bempomaa and Acquah (2014), and Wongnaa and Awunyo-Vitor (2019) revealed in separate studies that farmers averagely receive agricultural extension and training services once every planting season. Abdulai et al. (2018) reported that farmers receive between one and four extension visits per planting season with a mean of 3.07. The results is 50% less the mean number of visits and trainings received by farmers. The number of visits and training indicates increasing extension access is significant and can lead to adoption of new agricultural technological innovations to improve production. According to Gautam (2000) and Everson (2001) a well-functioning agricultural extension system improves the production of food crops, and offers a great opportunity to smallholder farmers to get higher income.

Farm Size cultivated to Maize by Farmers

The sizes of maize farms of farmers in the 2019 cropping season are presented in Table 18. The results indicate that majority (56.70%) of the farmers cultivated between 1.0ha and 3.9ha during the 2019 cropping season. More than one third (36.70%) of the farmers cultivated less than 1.0ha to maize. Generally, the farmers cultivated 0.4ha to 6.0ha to maize. The mean farm size of 1.60ha was cultivated by the 150 maize farmers during the 2019 planting season. The results are consistent with the findings of Abdulai et al. (2017) who found that farm sizes of maize farmers ranged between 0.2ha and 24ha.

Table 18: Size of maize cultivated by Farmers in 2019 (ha)

Farm size cultivated	Tolon District		Mion District		West Mamprusi		Overall sample	
	Freq	%	Freq	%	Freq.	%	Freq.	%
< 1.0ha	35	23.33	11	7.33	9	6.00	55	36.70
1.0 – 3.9ha	14	9.33	34	22.66	37	24.66	85	56.70
4.0 – 6.0ha	1	0.66	5	3.33	4	2.66	10	6.70
Total	50	33.33	50	33.33	50	33.33	150	100

Source: Field data, Asante (2020). n = 150. Mean farm size = 1.60ha, S.D = 1.11ha, Range = 0.40ha to 6.00ha.

The mean farm size of farmers in this study was consistent with the findings of Addai and Owusu (2014) and Abdulai et al. (2018) who in separate studies recorded mean farm sizes of 1.71ha and 1.76ha respectively. Higher mean farm sizes 3.21ha and 2.7ha were, however, recorded by Abdulai et al. (2017) and Wongnaa and Awunyo-Vitor (2019). Analysis of the results indicated that farmers in the study area were working on smaller farm holdings. This confirmed the assertion of Nyanteng and Seini (2000) that more than 90

percent of staple food produced in Ghana came from farmers operating on smaller farm holdings of 3ha or less. It is therefore not far from right to infer that maize production in the study area is on small scale basis.

Hence, the farmers can be classified as smallholders because according to Chamberlin (2007), small land holding is the most direct indicator of who smallholder farmers are. MoFA (2017) argued that, smallholder farmers dominate Ghana's agricultural sector with about 90% cultivating farm sizes of less than 2ha. It is worth noting that the situation of farmers cultivating small land holdings is not only limited to Ghana but also in other African countries. Mulwa et al. (2009), Onubuogu et al. (2014), Abdulai and Abdulai (2016), and Makate et al. (2017) reported of small farm holdings by farmers in Kenya, Nigeria, Zambia, and South Africa respectively.

Yield of Maize Harvested by Farmers (Mt/ha)

Results on maize harvested by farmers in the that study area during the 2019 cropping season is presented in Table 19. The results indicated that nine out of every ten farmers (90%) harvested less than 1.0Mt maize on every hectare of land. Farmers harvested between 0.02Mt and 2.8Mt on every hectare of land. The mean yield of maize harvested was 0.51Mt per ha (standard deviation = 0.43Mt/ha). The yield of maize recorded in this study was lower than those reported by Abdulai et al. (2018, 2017) and Wongnaa and Awunyo-Vitor (2019) i.e. 2.0Mt/ha and 2.2Mt/ha respectively in Northern Ghana. The average maize yield per hectare obtained in this study was 90% lower than Ghana's expected possible yield of 5.5Mt/ha (MoFA, 2017). The yield of maize harvested by farmers in Zambia was higher (92%) compared with that of farmers in this study (Abdulai & Abdulai, 2016). The lower maize yield recorded by farmers in this

study could be attributed to effects of climate change (AGRA, 2018) and the incidence of FAW which according to Day et al. (2017), accounted for 45% of yield losses.

Table 19: Yield of Maize harvested by Farmers in 2019 Cropping Season (Mt/ha)

Yield of maize in Mt/ha	Tolon District		Mion District		West Mamprusi		Overall sample	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%
< 1.0	49	32.66	42	28.00	44	29.33	135	90.00
1.0–2.0	0	0.00	7	4.66	6	4.00	13	8.70
2.1–3.0	1	0.66	1	0.66	0	0.00	2	1.30
Total	50	33.33	50	33.33	50	33.33	150	100

Source: Field data, Asante (2020). n = 150. Mean yield = 0.51Mt/ha, S.D = 0.43Mt/ha, Range = 0.02Mt/ha to 2.8Mt/ha.

Adu et al. (2014) posited that farmers in the Guinea Savanna Agro-ecological zone can obtain maize yield of 4.5-7.5Mt/ha if they adopt the good agronomic activities recommended by the Savannah Agricultural Research Institute of Ghana. The recommended good agronomic practices include fertilizer application complemented with organic manure for soil nutrition and conservation management, crop rotation, intercropping of maize with leguminous crops, planting improved maize seed varieties, weed control and mechanical soil ploughing before planting (Adu et al., 2014). However, farmers in the study who did not accommodate the good agronomic practices were unable to improve the crop yield in the face of climate emergency challenges and incidence of the FAW in the agro-ecological zone.

Income of Farmers from the sale of maize in 2019

Table 20 represents the results of the study on income farmers received from maize sales. The results showed that eight out of every ten (82.60%) farmers received between GH¢ 55.00 to GH¢ 1,999.00 from the sale of maize in 2019. The farmers received an average of GH¢ 1,418.33 (Standard deviation = GH¢ 1,282.54). The standard deviation indicated that there were variations in the income of farmers from the sale of maize. Analysis of the results showed that the money earned by the farmers from the sale of maize was consistent throughout the research area.

Abdulai et al. (2017) and Abdulai et al. (2018) studied income of farmers from the sale of maize in the northern part of Ghana and concluded that on the average, farmers received GH¢ 1,229.50 and GH¢ 1,234.74 respectively, per annum. Esoko Ghana (2019) posited that in a free market economy such as that which operates in Ghana, prices of agricultural commodities fluctuate during the year. Therefore, the amount of money farmers make from selling maize is determined by the time of year the item is sold.

Table 20: Income of farmers from the sale of maize in 2019 (GH¢)

Income from Maize	Tolon District		Mion District		West Mamprusi		Overall sample	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%
< 1000	26	17.33	16	10.66	20	13.33	62	41.30
1000-1999	23	15.33	19	12.66	20	13.33	62	41.30
2000 - 2999	0	0.00	8	5.33	5	3.33	13	8.70
>=3000	1	0.66	7	4.66	5	3.33	13	8.70
Total	50	33.33	50	33.33	50	33.33	150	100

Source: Field data, Asante (2020). n = 150. Mean income = GH¢ 1,418.33, S.D = GH¢ 1,282.54, Range = GH¢ 55.00 to GH¢ 8,400.

Land holding arrangements used by farmers

Table 21 presents the land holding arrangements operated by maize farmers. Generally, across the three study districts, close to nine-tenth (90%) of the number of farmers cultivated maize on family land. A few of them rented the land (6.70%) while 6.00% cultivated on farm lands on lease basis. The results differ from the findings of Amanor-Boadu et al. (2015) who on land holding arrangements for agricultural production survey in the Northern Regions of Ghana determined that majority (72%) out of the 1,120 farmers sampled owned farm lands. About a quarter (24%) indicated that the land was family owned, whilst a few (3%) cultivated community-owned land.

Table 21: Land holding arrangement used by farmers

Land holding	Tolon District		Mion District		West Mamprusi		Overall Sample	
	Freq	%	Freq.	%	Freq.	%	Freq.	%
Family land	42	28.00	46	30.66	43	28.66	131	87.30
Rent	5	3.33	4	2.66	1	0.66	10	6.70
Lease	3	2.00	0	0.00	6	4.00	9	6.00
Total	50	33.33	50	33.33	50	33.33	150	100

Source: Field data, Asante (2020).

n = 150.

Amanor-Boadu et al. (2015) had conceded that the findings of their study were a deviation from the conventional land ownership in Ghana, where a large proportion of land was under customary or community ownership. Diaw (2005) asserted that rural lands in Northern Ghana were predominantly under the administration of family heads. There is renewed interest by individuals to

invest in land for agricultural purposes in recent years in Northern Ghana (Bugri & Yeboah, 2017).

Main Sources of Income by Maize Farmers

The main sources of income of the maize farmers are presented in Table 22. The results indicated that farming was the primary source of income of the majority (73.30%) of farmers in all the three study districts. Livestock rearing was a subsidiary venture. Less than one quarter (16.00%) indicated that farming was complemented by petty trading and other incomes sources from masonry, carpentry, butchering, tractor operation and motor bicycle mechanical repairs. It is worth noting that (6.70%) of the farmers depend on official job engagements in public and private organizations for monthly income.

Table 22: Main sources of income by Maize Farmers

Sources of income	Tolon District		Mion District		West Mamprusi		Overall sample	
	Freq	%	Freq	%	Freq.	%	Freq.	%
Faming	30	20.00	42	28.00	38	25.33	110	73.30
Trading	4	2.66	2	1.33	0	0.00	6	4.00
Both	11	7.33	4	2.66	9	6.00	24	16.00
Official Job	5	3.33	2	1.33	3	2.00	10	6.70
Total	50	33.33	50	33.33	50	33.33	150	100

Source: Field data, Asante (2020).

n = 150.

The results contradicted the findings of Dary and Kuunibe (2012) who revealed that 83% of farmers sampled engaged in petty trading as main source of income whilst 17% depended on only farming for income. The results of this study mirrored the findings of Anang and Yeboah (2019) who established that 43% of the farmers sampled in a survey earned income from off-farm activities

such as petty trading and official job. The assertion that farmers in Northern Ghana also earn income from carpentry, masonry, animal slaughter, tractor operating and motor bicycle repairs (Dary & Kuunibe, 2012) and livestock production (Baidoo et al., 2016) was also confirmed by the study. Considering that off-farm activities provide alternative sources of income for crop farmers, the study agreed with the recommendations of Sienso et al. (2015) that stakeholders in agriculture including extension agents, NGOs, opinion leaders and policy makers should implement programmes aimed at helping farmers to identify alternative sources of income to support their households.

Chapter Summary

This chapter presented results on farmer and farm-related characteristics of respondents. Frequencies, percentages, measures of central tendencies, and cross-tabulation were utilized to analyze the data. The outcome showed that, most (56.7%) of the farmers were males, with an average age of 41 years and a lot of experience (Mean experience =18.70 years) in maize production. Also, an overwhelming majority (93.30%) of the farmers were married, more than two thirds (76%) had no formal education whilst most (78.60%) of the educated ones had pre-tertiary education from Primary to Senior High School. Furthermore, nine out of every ten (90%) farmers harvested less than 1.0Mt maize on an average farm size of 1.60ha and received an amount average of GH¢ 1,418.33 from the sales. The farmers received an average of seven extension visits during the planting season because farming was their primary occupation and main source of income of majority (73.30%) of them working on family lands.

CHAPTER FIVE

FARMERS' AWARENESS OF APPLICATION OF DRONE TECHNOLOGY IN AGRICULTURE

Introduction

The drone is becoming an important technology being applied to improve agriculture, especially for the control of FAW in maize cultivation. Chapter Five presents the results and discussions on the level of awareness of maize farmers on application of drone technology in terms of the use of spraying, picture taking, land surveying, monitoring, security and others such as in oil, gas and mineral exploration. This study measured that awareness of maize farmers about drone technology in order to understand how farmers would accept the technology for the control of FAW in the study area.

Awareness (Seen or Heard) of Farmers of Drone Technology

Results presented in Table 23 indicate that only a fifth (19.93%) of the farmers had seen or heard of drone technology. Out of the number of farmers who had seen or heard of drone technology, ten were from West Mamprusi whilst eight were from Tolon and Mion Districts respectively. This is not surprising and much has not changed since 2013. Similar findings are that of Eyerman et al. (2013) which concluded from a survey of public perceptions about unmanned aircraft and the human element that the general public had a fairly low level of awareness of drone technology. Actually, the number (82.07%) of the respondents in this study who indicated that they had never heard or seen a drone was almost two times higher than the 44% recorded by Eyerman et al. (2013).

Table 23: Awareness of Farmers of the Drone Technology

Seen or Heard	Tolon District		Mion District		West Mamprusi		Overall sample	
	Freq.	%	Freq.	%	Freq.	%	Total	%
Yes	8	5.52	8	5.52	10	6.90	26	19.93
No	40	27.58	41	28.27	38	26.20	119	82.07
Total	48	33.10	49	33.79	48	33.10	145	100
Chi Squire value		df		Asymptotic p. value				
0.22		2		0.89				

Source: Field data (2020). n = 145. p > 0.05.

Comparable findings was reported by Reddy and DeLaurentis (2016) when they revealed that 93% of the respondents from the general public had heard about drones by watching movies and through the media. On the other hand, findings on awareness contradict Tahir et al. (2019) who found in Finland and Pakistan that only 4.81% from 187 participants had never heard about drone technology. The very low awareness about drone technology by the respondents of this study is consistent with the assertion of Aydin (2019) that there is the need to measure the awareness and actual knowledge about drone technology and its broader applications because without knowing how much the public know about the technology, it is difficult developing strategies to effectively manage the revolution of drones.

According to the chi-square analysis, there was no significant association between the farmers in the three districts in terms of awareness of drone technology (χ^2 value = 0.22, df = 2, p = 0.89) (Table 23). The result

implies that the level of awareness of maize farmers on the use of drone technology is the same in the three districts where the study was carried out. Therefore, the study failed to reject null hypothesis that there is no significant relationships between the farmers in the various districts and awareness of drone technology.

Awareness of Farmers of Application of Drone Technology

Majority (57.69%) of farmers who were aware of drones indicated that they had seen them being used to spray pesticides Table 24. At least four out of every 10 farmers were aware of drone technology, and had heard or seen the drone being used to take pictures (46.15%) and for film making (42.31%).

Table 24: Farmers' awareness of the different fields where drones are deployed

Level of awareness of drones	Tolon District		Mion District		West Mamprusi		Overall sample	
	Freq.	%	Freq.	%	Freq	%	Freq.*	%
Pesticides Spraying	3	2.10	6	4.13	6	4.13	15	57.69
Picture taking	5	3.45	2	1.38	5	3.45	12	46.15
Film making	5	3.45	1	0.69	5	3.45	11	42.31
Land surveying & Remote sensing	2	1.38	2	1.38	2	1.38	5	19.23
Monitoring Security	1	0.69	1	0.69	2	1.38	4	15.38
Medical supplies	1	0.69	1	0.69	1	0.69	3	11.54
Oil & Gas exploration	1	0.69	-	-	1	0.69	2	7.69
Mineral exploration	1	0.69	-	-	1	0.69	2	7.69

Source: Field data, Asante (2020).

n = 26. * Multiple responses

Other farmers were aware of the drone being used for land surveying and remote sensing (19.23%), for monitoring of security (15.38%), for distribution of medical supplies (11.54%), for oil and gas (7.69%) and for mineral (7.69%) explorations. The assertion can be confirmed that drones are deployed in many fields of endeavour (Hanssen, 2016; Puri et al., 2017), including being used by security services for security and law enforcement (Probst et al., 2017), as air ambulances for medical deliveries (Puri et al., 2017) and delivery services, for film and television industries (Ahirwar et al., 2019). The respondents, however, did not confirm the application of drones in disaster management, search and rescue, and wildlife monitoring (Ahirwar et al., 2019), humanitarian emergencies (FAO & ITU, 2018) and meteorological research (Hogan et al., 2017).

Sources of Awareness of Drone by Farmers

The sources of farmers' awareness of drones are presented in Table 25. Ten of the farmers (38.46%) became aware of drone technology when watching television. Attendance of church services, marriage and funeral ceremonies (34.70%) and the security services during security surveillance (26.92%) were the major sources of farmers' awareness of drone being used. The main themes which emanated from the groups discussion on the source of awareness of the farmers of drone technology included attending ceremonies such funerals, weddings, church services, watching television and observing state agencies using it for surveillance. The results is buttressed with the following quotations.

Table 25: Sources of farmers' awareness of drone deployment fields

Source of awareness	Tolon District		Mion District		West Mamprusi		Overall sample	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%
Television	-	-	4	15.38	6	23.08	10	38.46
Church services / Funerals	4	15.38	2	7.69	3	11.54	9	34.62
Security surveillance	4	15.38	2	7.69	1	3.82	7	26.92
Total	8	30.77	8	30.77	10	38.46	26	100

Source: Field data, Asante (2020). n = 26.

The main sources of awareness of the farmers of drone technology from the qualitative data included attending church, funerals and marriage ceremonies, watching television and observing state agencies using it for surveillance. These results is consistent with the quantitative data. To support the point the that the drone was seen during ceremonies, a farmer at Salankpang in the Mion District, indicated that, *“During the final funeral rites of Yaa Naa Mahamadu Abdulai and Yaa Naa Yakubu Andani II, I saw the members of the security services and the media houses flying equipment like an ‘aero plane’ in Yendi”*. Another farmer also noted that, *“I saw ‘aero planes’ during the investiture of the new Yaa Naa Abubakari Mahama at Yendi, I saw a police officer and a young man from a TV station holding mobile phones and using them to control aero planes”*. On the use of the drone for surveillance, a farmer at Kukua also noted *“Officials of the Northern Electricity Distribution Company using ‘aero planes’ for monitoring electrical cables in Walewale”*. Similarities can be drawn between both quantitative and qualitative results. The result mirrors that of Reddy and DeLaurentis (2016) who found 93% of the

respondents in a study indicating their awareness of drones by watching television. Also consistent with this study was the findings of Aydin (2019) who concluded that the public learned about drones from mainstream media and watching movies or television series.

Participation of Farmers in Drone Agricultural activities

The FAO and the ITU (2018) posited that the application of drone technology in agriculture is growing at a very fast pace in crop production, disaster risk reduction, fisheries, forestry, early warning systems and wildlife conservation. Only five farmers had engaged in agricultural events where drones were deployed Table 26. Of the five farmers who had participated in drone-applied agricultural activities, one was from Tolon District while two each were from Mion and West Mamprusi Municipalities. Farmers participated in activities organized by the Ministry of Food and Agriculture, a Research Institution, and Non-Governmental Organizations, to name a few. During the focus group discussions, one of the female farmers in Kukua remarked, *“I participated in a programme organised by an NGO to expose farmers to the application of drones to accurately estimate farm size and crop yield.”* The findings mirror that of Torres-Rua (2017) who found out that drones are used for estimation of farm size and crop yield.

The application of drones for estimating farm sizes and crop yields was corroborated by one of the farmers in the Tolon District. He, however, noted that he rather participated in a programme organized by the Ministry of Food and Agriculture. Since the farmers corroborated NGO interactions with MoFA in the discussions, this showed that they did not own drones. Another farmer in the Mion District mentioned something similar during the group discussion; *“I*

was invited to a training programme by a research institution on using drones for monitoring farm animals like small ruminants and a large herd of cattle”.

The results are consistent with those of Ahirwar et al. (2019) who concluded that drones are used for monitoring cattle herds.

Table 26: Participation of Farmers in Drone applied agricultural activities and Institutions who deployed the drones

Participati -on in Agric activies.	Tolon District		Mion District		West Mamprusi		Overall sample	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%
Yes	1	3.82	2	7.69	2	7.69	5	19.23
No	7	26.92	6	23.08	8	30.77	21	80.77
Total	8	30.77	8	30.77	10	38.46	26	100
Institutions								
NGOs	-	-	1	20.00	2	40.00	3	60.00
MoFA	1	20.00	-	-	-	-	1	20.00
Research Institution	-	-	1	20.00	-	-	1	20.00
Total	1	20.00	2	40.00	2	40.00	5	100

Source: Field data, Asante (2020).

n = 26 and n = 5.

It is worth noting that more than eight out of every ten farmers (80.77%) participated in an agricultural programme where a drone was deployed for the very first time. The results are consistent with the well known assertion that drones are used for agricultural activities (Barbedo, 2019; Barbedo & Koenigkan, 2018; Beloev, 2016; Handique et al., 2017; Hogan et al., 2017; Zhang & Kovacs, 2012) a position confirmed by respondents in this study. Probst et al. (2017) postulated that at the heart of meeting the growing global food demand lies the introduction of new, demand-driven and cutting-edge

technologies in agriculture. The authors argued that these new technologies have been used to power and enhance existing rudimentary tools and methods with evidence of different applications already deployed on farms. Probst et al. (2017) concluded that an example of new technologies pushing the expansion of precision agriculture is drone technology in recent years.

Chapter Summary

Chapter five presented the results on the level of awareness of maize farmers on the application of drone technology in agriculture. Both quantitative and qualitative data was collected. Frequencies, percentages, chi-square techniques and thematic analysis were utilized to analyze the data. The results showed that one-fifth (19.93%) of the farmers were aware of drone technology with 38.46% gaining their awareness from watching television. The chi-square test revealed that the level of awareness of maize farmers on the use of drone technology is the same in all the three study districts. A majority (57.69%) of farmers were also aware that the drone is used for spraying pesticides. That notwithstanding, only five of the farmers had taken part in agricultural activities where drones were utilized.

CHAPTER SIX

PERCEPTION OF FARMERS ABOUT THE BENEFITS OF DRONE TECHNOLOGY FOR CONTROL OF FALL ARMY WORM

Introduction

The benefits of technology are important for enhancing its acceptance (Mndzebele, 2013). Technology has proven to be highly beneficial in the agricultural sector over time (Mairura, 2016). Farmers can now grow crops in areas which were previously considered inaccessible for cultivation, but can now be utilized courtesy agricultural technology (Ahirwar et al., 2019). Chapter Six presents results of the study that sought to examine the perception of farmers of the benefits of drone spraying services for Fall Armyworm control and the underlying factors that preceived the benefits.

Description of the Spraying Drone by Farmers

The study's primary goal was to look into farmer adoption of the technology. Recognizing that farmers were familiar with the use of drones in agriculture, a video of spraying drone controlling FAW was shown to farmers. This section sought to find out the knowledge of the farmers about the drone after application. The results presented in Table 27 reveal that all the 145 farmers who watched the video could describe the characteristics of the drone very well. All indicated that it has a tank/container for holding and storing pesticides.

Apart from one respondent, the rests (99.3%) observed that the drone had nozzles for discharging the pesticides onto the crops. Only five out of 145 farmers (3.45%) could not indicate that the drone has propellers/wings for

flying. A majority of the farmers (95.20%) observed that the drone has stands/legs to land safely and a remote control operated by the pilot whilst same findings were recorded by farmers after observing the live drone application of pesticide on the fields. The description of the spraying drone by the farmers mirrors the description provided by Lou et al. (2018).

Table 27: Farmers' description of the Spraying drone

Farmers' description of the Spraying drone	Video application		Live application	
	Freq.*	%	Freq.*	%
It has tank/container to store pesticides	145	100.00	105	100.00
It has nozzle for discharging the pesticides on the field	144	99.30	105	100.00
The drone has propellers/wings used to fly over the field	140	96.60	105	100.00
It has stands/legs to land safely	138	95.20	105	100.00
It is remotely controlled	138	92.20	105	100.00

Source: Field data, Asante (2020). Video of Drone application (n = 145), Live Drone application (n = 105). *Multiple responses

Perceptions of Farmers of the Benefits of Drone Technology for control of FAW

Table 28 shows farmers responses on the benefits of drone spraying services for Fall Armyworm control. After the maize farmers had watched the video, their perceptions of the benefits of deploying drone technology for control of FAW was, generally, 'very high' (Composite mean = 8.53). The first five bases for the perceived benefits of drone for Fall Armyworm control were; ease of application (Mean = 9.08, S.D = 1.49), reduced negative effect on health (Mean = 9.06, S.D = 1.47), the technology requires less labour (Mean = 9.03, S.D = 1.64), it saves time (Mean = 8.99, S.D = 1.73) and the technology

enhances the application of pesticides (Mean = 8.89, S.D = 1.68). Although perceived to be beneficial, the least among the rating was the fact that the drone spraying services will not necessitate change in attitude of maize (Mean = 7.69, S.D = 2.76) and belief of farmers (Mean = 7.97, S.D = 2.44).

The column in Table 28 on Live Application shows how farmers perceived the benefits after they had had the opportunity of observing live drone application of pesticides on the field. Similarly, the farmers generally regarded 'very high' the advantage of drone application for FAW control (Composite mean = 8.78). However, the three bases of perceived benefits were the ability of the drone technology to save time (Mean = 9.40, S.D = 1.07), the drone requires less labour (Mean = 9.26, S.D = 1.32) and makes pesticides application easier (Mean = 9.09, S.D = 1.25). The last basis was drone technology saves money (Mean = 8.04, S.D = 2.13) and drone technology fits well with pesticides application (Mean = 8.42, S.D = 1.62).

During the FGDs, respondents were unanimous in acknowledging that the drone provides enormous benefits for control of FAW. Four overarching themes emerged from the focus group discussions: the technology is effective for control of FAW, faster, protects the safety of the environment and less labourous. Regarding the effectiveness of the drone for control of FAW, a participant in Nyankpala remarked that, "*I think the drone would be very effective for controlling the FAW because of its ability to fly over the field and enabling it to target the pests that may be hiding in the leaves of the maize.*" Another farmer in Kukua also noted that, "*The drone can sustain in the air over highly infested FAW field and spray pesticides at the exact location of the infestation.*" Concerning the speed of the drone during spaying, one respondent

from Loagri noted that, *“The drone is very fast and can cover a large area in a very short period of time during spraying; that means, I don’t have to spend the whole day in the farm spraying pesticides with the drone”*.

Pertaining to the safety of the environment, the participants agreed that the volume of water and pesticides utilized by the drone during spraying is in small quantities hence limit the amount of pesticides exposed to the environment. Also, the ability of the drone to precisely spray exact quantity of pesticides targeted at the FAW, reduces the effect of the pesticides on other insects in the environment. One somewhat obvious finding that came out of the FGDs was that the farmers perceived spraying pesticides with drone as less labourous. This finding is not surprising because of the labour intensive nature of most agricultural activities including spraying pesticides. When farmers described the specific challenges with pesticides spraying, they expressed general perspectives of the less labourous nature of pesticides spraying using the drone.

To buttress this point, a farmers in Kukua indicated that, *“I have seen that with the drone I don’t have to carry the knapsack sprayer on my back for several hours in the hot sunshine to spray pesticides to control the FAW.”* Another farmer in Kplijine indicated that, *“Pesticides spraying is very labourous and labour intensive; apart from carrying the tank on your back, you also have to exert pressure with your right hand such that by the time you complete the spraying you would be very tired.”* One woman in Loagri also added the need for adequate supply of water for spraying which increased the labourous nature of spraying, she said; *“I can see that with the drone I don’t have to carry too much water to the farm for spraying. The drone will reduce*

the amount of work I have to do anytime we have to spray pesticides to control the FAW”.

The findings mirror those of Ahirwar et al. (2019) who concluded that drone application of pesticides on stressed fields is done due to its accuracy, extraordinary speed and ability to cover large areas in a short period of time with limited human support. The spraying drone is estimated to be 40–60 times faster than manual spraying (UAV Systems International, 2019). The drone sprayer has come up as a reliable means of controlling FAWs because it uses less volume of pesticides, it is easy to use and fits well with the way crop protection products are applied in the field (Garre & Harish, 2018). The drone for spraying FAW-infested maize fields improves the coverage of the crop protection product on target insect without excessive spillage beyond reach of the target plots (De Rijk et al., 2018).

The drone technology for the control of FAW can be perceived as a superior method of pesticide application because it offers innovative cultivation opportunities in the form of improved productivity and increased operational efficiency (Mairura, 2016; Mndzebele, 2013). This observation was confirmed by the study of Ahirwar et al. (2019) who found out that the use of UAVs for spraying minimises the effects of pesticides on the environment and other organisms in the ecosystem, as well as reducing human exhaustion associated with other forms of FAW control. The use of spraying drone for the control of FAW is consistent with the values, attitude and beliefs required for control of pests (Immorlica et al., 2007; Mairura et al., 2016). Mndzebele (2013) argued that, the acceptance of drone spraying services for FAW control would not require a change in attitude, belief and behaviour of the technology users.

Table 28: Perception of farmers of the Benefits of Drone Technology for control of FAW

Video of Pesticides Application (n = 145)			Live Pesticides Application (n = 105)		
Benefits	Mean	S. D	Benefits	Mean	S. D
Makes pesticides application easy	9.08	1.49	Saves time	9.40	1.07
Reduces negative effect on my health	9.06	1.47	Less labour involved	9.26	1.32
Less labour involved	9.03	1.64	Makes pesticides application easy	9.09	1.25
Saves time	8.99	1.73	Reduces negative effect on health	9.04	1.18
Pesticides application effective	8.89	1.68	Pesticides application effective	8.99	1.27
Rduces negative impact of pesticides on the environment	8.87	1.62	Pesticide spraying methods that farmers are familiar with are superior	8.92	1.52
Pesticide spraying methods that farmers are familiar with are superior	8.79	1.75	Less wastage of pesticides	8.74	1.14
Exact quantity of pesticides applied	8.51	1.94	It does not necessitate a change in farmers' pesticide application beliefs	8.71	1.47
Fits well within the way pesticide is applied in my area	8.51	1.94	Less amount of pesticides used	8.70	1.30
Less wastage of pesticides	8.48	1.79	It does not necessitate a change in farmers' attitudes towards pesticide use	8.69	1.55
Applied pesticides precisely kill caterpillar FAW	8.30	2.17	Applied pesticides precisely to kill caterpillar FAW	8.69	1.46
It does not necessitate a change in farmers' pesticide application behvaiour	8.18	2.40	It does not necessitate a change in farmers' pesticide application behvaiour	8.66	1.59
Saves money	8.08	2.33	Exact quantity of pesticides applied	8.63	1.39
Less amount of pesticides used	8.06	2.26	Pesticides' detrimental envirnmental impact is reduced	8.46	1.89
It does not necessitate a change in farmers' pesticide application beliefs	7.97	2.44	Aligns perfectly with how pestides are used in community	8.42	1.62
It does not necessitate a change in farmers' attitudes towards pesticide use	7.69	2.76	Saves money	8.04	2.13
Composite mean	8.53		Composite mean	8.78	

Source: Field data, 2020. n = 145. Scale: 1 = Very low to 10 = Very high

Differences between Farmers' perception of the benefits of drone technology for the control of FAW after watching Video, and Live operation of drone

Table 29 presents statistics (mean, standard deviation and p-value) of Paired Sample T-test that examined the difference between farmers' perceived benefits after watching video, and live operation of drone technology for control of FAW. The maize farmers did not differ significantly ($t = -1.29$, $df = 100$, $p\text{-value} = 0.20$) in their perception of the advantages of drone spraying services for Fall Armyworm control after watching the video and live operation of drone. The eta squared statistic (0.02) implied small effect size (Cohen, 1988, pp. 284-287). The result indicated that the perception of the maize farmers of the benefits of the drone technology for control of FAW did not change significantly after watching the video and live drone insecticides application for Fall Armyworm control. This implies that the videos produced a similar effect like the live presentation. Therefore the use of video, if properly presented, can be used to substitute live presentation of extension messages. Hence, null hypothesis which stated that farmers did not differ in their perception of the benefits of drone for control of FAW in the study area during video and live presentation is accepted.

Table 29: T-test results on perception of farmers of the benefits of Drone Technology for the control of FAW after video and live presentation

Drone Applications	Mean	s.d	Mean Diff.	Stand. Mean Error	t	df	*p-value
Video of application	8.57	1.15	-0.17	0.13	-1.29	100	0.20
Live application	8.74	0.97					

Source: Field data, Asante (2020). * $p > 0.05$. $n = 105$. Scale: 1 = Very low to 10 = Very high

Factors Underlying Farmers' Perception of the Benefits of Drone Technology for Control of FAW

Principal component analysis (PCA) was utilized to examine the underlying factors explaining the perception of farmers of the advantages of drone spraying services for Fall Armyworm control. The data set was assessed for its suitability for factor analysis before performing the PCA. The correlation matrix of the data set was inspected which revealed a number of coefficients greater than 0.3. The Kaiser-Meyer-Olkin value of sample size adequacy was 0.789, greater than the approved value of 0.6 (Pallant, 2016). The Bartlett's Test of Sphericity also revealed arithmetically significance indicating that the correlation matrix supports the factorability of the variables (Tabachnick & Fidell, 2013).

The PCA showed the presence of five components with eigenvalues greater than one (1), explaining cumulative 70.15% of the variations (component 1 = 34.86%, component 2 = 12.06%, component 3 = 8.91%, component 4 = 7.62% and component 5 = 6.704). Analysis of the screeplot, following the third component, there was a break. The three components were chosen for further examination using Catell (1966) scree test (Figure 14 Appendix E). With help of Monte Carlo PCA, Parallel Analysis was computed to confirm the number of factors. The results showed that only three components had eigenvalues greater than the corresponding criterion values for the 100 randomly generated data matrix of the same sample size (16 variables x 145 maize farmers) (Table 46, Appendix E).

Three factor solution explained composite effect of 55.83% of the variation with component 1 explaining 34.86%, component 2 explaining

12.06% and component 3 explaining 8.91% of the variation. The correlation matrix of the three factors was examined to assess the rotation adequacy of the PCA. Utilizing the Davis (1971) convention for explaining the magnitude of correlation coefficient (Appendix A), there was a low positive intercorrelation between component 1 and component 2 ($r = 0.21$), low negative intercorrelation between component 2 and component 3 ($r = -0.28$) while a moderate negative intercorrelation was recorded between component 1 and component 3 ($r = -0.33$) (Davis, 1971). When oblique rotation was requested, components interpreted as environmental benefits and social benefits correlated ($r = -0.33$), however, because the correlation was moderate and limited only to the pair of factors and because the rest of the correlations were low, varimax orthogonal rotation was performed to help with the interpretation of the three components.

Table 30 shows the variable loadings on factors, communalities, and percents of variance and covariance. The variables were ordered and grouped by the size of loading to facilitate interpretation. The suggestive interpretative labels for the factors underlying farmers' perceived benefits of drone for control of FAW were technical benefits, economic benefits and social benefits. The factors exhibited a number of strong loadings. Seven of the variables loaded strongly on technical benefits, five on economic benefits and four on social benefits. Loadings below 0.45 (20% of variance) are replaced by zeros. In general the three factors underlying farmers' perception of the advantages of drone spraying services for Fall Armyworm control were: technical benefits (e.g. less wastage of pesticides, drone makes pesticides application easy), economic benefits (e.g. the technology saves money, saves time) and social

benefits (e.g. technology does not necessitate a change in farmers' attitude toward pesticide use).

Table 30: Factor Loadings, Cummunalities (h^2) and Percents of Variance and Covariance for Principal Component Analysis and Varimax Rotation on perception of the benefits of drone for FAW control

Benefits	C ₁	C ₂	C ₃	h^2
Less wastage of pesticides	0.76	0.00	0.00	0.62
Makes pesticides application easy)	0.68	0.00	0.00	0.59
Applies pesticides to precisely kill caterpillar FAW	0.67	0.00	0.00	0.48
Pesticide application is effective	0.66	0.00	0.00	0.64
Less amount of pesticides are used	0.63	0.00	0.00	0.46
Reduces negative effect on health of farmers	0.53	0.00	0.00	0.49
Exact quantity of pesticides applied	0.51	0.00	0.00	0.28
Saves money	0.00	0.77	0.00	0.62
Superior to other methods of pesticides application known to farmers	0.00	0.76	0.00	0.62
Saves time	0.00	0.73	0.00	0.66
Fits well within the way pesticide is applied in my area	0.00	0.65	0.00	0.56
Less labour involved	0.00	0.50	0.00	0.51
It does not necessitate a change in farmers' attitudes toward pesticise use	0.00	0.00	0.83	0.69
It does not necessitate a change in farmers' pesticide application beliefs	0.00	0.00	0.82	0.76
It does not necessitate a change in farmers' pesticide application behaviour	0.00	0.00	0.59	0.44
Reduces the negative impact of pesticides on the environment	0.00	0.00	0.53	0.52
Sum of Squared loadings (SSL)	4.10	3.15	3.83	
Percent of variance	25.59	19.69	23.93	
Percent of covariance	37.04	28.46	34.60	

Source: Field data, Asante (2020). n = 145

Differences in the factors underlying Farmers' perception of the Benefits of Drone Technology for control of FAW in the Three Districts

Correlations matrix, means and standard deviation of the three factors are presented in Table 31. Adopting the Davis (1971) convention, the results indicated that a positive moderate relationship between technical benefits and economic benefits ($r = 0.43$, $p = 0.00$) and social benefits ($r = 0.30$, $p = 0.00$), however, the relationship between economic and social benefits was substantial ($r = 0.52$, $p = 0.00$). Pallant (2016) argued that correlations of 0.80 or above would imply the violation of the assumption of multicollinearity. Means of the factor used in the analysis were technical benefits (mean = 8.68, s.d = 1.15), economic benefits (mean = 8.75, s.d = 1.27) and social benefits (mean = 8.22, s.d = 1.65).

Table 31: Correlations matrix, means and standard deviation of the three orthogonal principal components

S/N	Variables	1	2	3	Mean	s.d
1	Technical benefits	1			8.68	1.15
2	Economic benefits	0.43**	1		8.75	1.27
3	Social benefits	0.30**	0.52**	1	8.22	1.65

Source: Field data, Asante (2020). n = 143

A one-way multivariate analysis of variance (MANOVA) was performed on three factors of benefits of drone technology (technical benefits, economic benefits and social benefits) as dependent variables and the study districts as independent variable (Tolon District, Mion District and West Mamprusi Municipality) to examine the difference in the perception of the farmers on benefits of drone spraying services for Fall Armyworm control. The

order of entry of the independent variable was Tolon District (46 cases), Mion District (47 cases) and then West Mamprusi Municipality (50 cases). The total sample size of 145 was reduced to 143 with the deletion of two cases which recorded high Mahalanobis distance of 22.44 and 19.11 compared to the recommended critical value (16.27) for three dependent variables (Pallant, 2016; Tabachnick & Fidell, 2013). There was however, no univariate within-cell outliers at $p < 0.01$.

The assessment of the Kolmogorov-Smirnov Normality Test which calculated the normality distribution of the scores indicated that, assumptions of normality of all the three dependent variables was violated (Table 32). A non significant value (sig. > 0.05) indicate normality. However, all three dependent variables recorded sig. values of 0.00, signifying the violation of the normality assumption, a situation, Pallant (2016) suggested is common with studies with large sample sizes.

Table 32: Kolmogorov-Smirnov Normality Tests and Box's M

Kolmogorov-Smirnov Normality Test			
Factors	Statistic	df	sig.
Technical benefits	0.13	143	0.00
Economic benefits	0.16	143	0.00
Social benefits	0.14	143	0.00
Box's Test of equality of Covariance Matrices			
Box's M	F	df	sig.
23.34	1.88	12	0.03

Source: Field data, Asante (2020).

n = 143

Table 32 also presented the Box's Test of equality of Covariance Matrices test which indicated that the assumption of homogeneity of variance-

covariance matrix across the three districts was adequate. The results showed that there is no concern as Box's M (23.34) ($F = 1.88$) was not significant ($p(0.03) > \alpha(0.001)$), demonstrating that there was no significant differences between the covariate matrices, hence, the assumption of homogeneity of variance-covariance was not violated. The preliminary analysis also showed that the assumptions of both linearity and multicollinearity were adequate. Using Pillai's Trace test at an alpha level of 0.05 due to the unequal number of farmers in each cell, the MANOVA showed a significant multivariate effect on the factors underlying the benefits of drone spraying services for Fall Armyworm control in the three districts, Pillai Trace = 0.15, $F(6,278) = 3.72$, $p < 0.001$, partial eta squared = 0.074. The significance of F points out that there are significant differences among the farmers in Tolon, West Mamprusi, and Mion on a linear combination of the three factors.

The multivariate Partial Eta Squared (η^2) = 0.074 represents approximately 7% of the multivariate variance of the technical, economic and social benefits of drone spraying services for FAW control is explained by the district factor. The variance of 7% is denoted as a small effect according to generally accepted criteria posited by Cohen (1988). The null hypothesis which indicated that the pattern of responses of maize farmers in the three districts had no systematic effect on the optimal linear combination of the technical, economic and social benefits of drone application for the control of FAW is not retained.

When the results of the factors were examined separately, the only difference to reach statistical significance using a Bonferroni adjusted alpha level of 0.017 based on the number of dependent variables was perceived

technical benefits $F(2,140) = 6.81, p = 0.002$, partial eta squared = 0.089 with confidence limits from 8.63 to 9.25. An examination of the mean scores showed that maize farmers in West Mamprusi Municipality (Mean = 8.94, SE= 0.16) reported higher perceived technical benefits of drone technology for control of FAW than by maize farmers from Mion (Mean = 8.89, SE = 0.16) and Tolon (Mean = 8.19, SE = 0.16) districts respectively.

The results of the Bonferroni Post-Hoc multiple comparisons (Table 33) of the mean score for maize farmers in the West Mamprusi Municipality of the perceived technical benefits of drone technology (Mean = 8.94, s.d = 1.10) was significantly different from the mean score of maize farmers in the Tolon District (Mean = 8.19, s.d = 1.24) but did not differ significantly from the mean score of maize farmers in the Mion District (Mean = 8.89, s.d = 0.96) at 0.017 alpha level. Also, the perception of the maize farmers in the Mion District was significantly different from farmers in the Tolon District at 0.017 significance level. The result implies, the perception of the farmers in the Tolon District of the technical benefits of the use of drone technology for the control of FAW was statistically different from the farmers in the West Mamprusi and Mion. The perception in the West Mamprusi and Mion Districts among the farmers was, however, the same.

Khurshid et al. (2018) posited that we can gain fresh insights into the dissemination of knowledge and technical advancement if we have a better grasp of innovation dispersion across locations and through social relationships. Talukder et al. (2019) also added that geographical locations have an impact on the adoption at the local level. Geographically people are more sensitive to

changes in gross benefits that occur at their locations (Wang & Lo, 2016). The findings show that there is a variation in the technical benefits of the technology.

Table 33: Bonferroni Post-Hoc multiple comparisons of Districts and the Perception of Technical benefits

District	District	Mean Diff.	SE	p. value	98.3% Conf. Interval	
					Lower Bound	Upper Bound
Tolon	Mion	-0.70*	0.23	0.008	-1.34	-0.06
	West Mamprusi	-0.76*	0.23	0.003	-1.38	-0.12
Mion	Tolon	0.70*	0.23	0.008	.06	1.34
	West Mamprusi	-0.05	0.22	1.000	-0.68	0.58
West Mamprusi	Tolon	0.75*	0.23	0.003	0.12	1.38
	Mion	0.05	0.22	1.000	-0.58	0.68

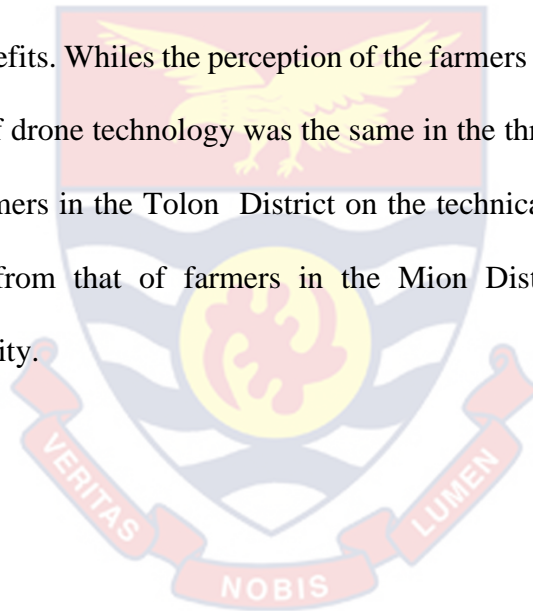
* $p < 0.017$. The mean difference is significant at the 0.017 level.

Source: Field data, Asante (2020). n = 143.

Chapter Summary

This chapter presented the results of the objective that sought to examine the perception of farmers of the benefits of drone technology for the control of FAW after watching video and live drone application of pesticides. The statistical tools used for analysing the quantitative data included: means, standard deviation, paired sample t-test, principal component analysis and multivariate analysis of variance. The qualitative data was analyzed using thematic analysis. The results showed that the maize farmers perceived the advantages of drone spraying services for Fall Armyworm control as: ease of

pesticides application, reduced negative effect on health of the sprayer, less labour required during pesticides application, time-saving nature and the fact that the technology enhances the application of pesticides application. The benefits perceived by the farmers are that: it does not necessitate a change in farmers' attitudes, and beliefs toward pesticide use because it saves money and fits well with pesticides application among the farmers. The results revealed that the farmers did not differ in the perception after watching both video and live drone application of pesticides. Farmers' perception of the technology's benefits are influenced by a number of factors which are its technical, economic, and social benefits. While the perception of the farmers on the economic and social benefits of drone technology was the same in the three districts, the perception of the farmers in the Tolon District on the technical benefits was statistically different from that of farmers in the Mion District and West Mamprusi Municipality.



CHAPTER SEVEN

PERCIEVED COSTS AND BENEFITS ANALYSIS FOR USE OF DRONE TECHNOLOGY AND KNAPSACK SPRAYER FOR CONTROL OF FAW

Introduction

This chapter presents the results and discusses the objective three which sought to compare the perception of the farmers on the costs and benefits of using drone technology and knapsack sprayer to control FAW in the study area.

Perceived Cost and Benefits of using Drone Technology and Knapsack Sprayer for control of FAW

Table 34 presents the perceived cost and benefits of using drone and knapsack for control of FAW. Generally, the farmers perceived a significant difference ($t = 3.91, p = 0.00$) in the cost and benefits of using the drone for control of FAW (composite mean = 6.06) compared to the use of knapsack (Composite mean = 5.51) after watching the video of pesticides application. The farmers perceived a significant difference ($t = 14.12, p = 0.00$) in the efficiency in the use of drone (Mean = 8.48, S.D = 2.22) compared to the knapsack (Mean = 4.32, S.D = 2.39) for control of FAW. Farmers also perceived significant difference in the performance ($t = 13, p = 0.00$) and ease of use ($t = 14.52, p = 0.00$) of the drone [(Mean = 8.37, S.D = 2.30), (Mean = 8.33, S.D = 2.61)] compared to the knapsack [(Mean = 4.40, S.D = 2.38), (Mean = 3.94, S.D = 2.36)] for control of FAW.

The farmers, on the other hand, perceived a significant difference in the cost and benefits of the use of knapsack in terms of its availability (Mean = 8.58, S.D = 2.19, $t = -18.78, p = 0.00$), effect of its weight on the sprayer (Mean =

8.32, S.D = 1.81, $t = -18.74$, $p = 0.00$), exertion of energy (Mean = 8.59, S.D = 1.89, $t = -17.99$, $p = 0.00$) and spillage of pesticides during spraying (Mean = 7.63, S.D = 2.16, $t = -12.63$, $p = 0.00$) compared to the drone for control of FAW. It is worthy of note that farmers perceived the cost and benefits of knowledge needed to operate the drone (Mean = 5.90, S.D = 3.23) and knapsack (Mean = 5.17, S.D = 3.07) to be the same ($t = 1.62$, $p = 0.11$). Data from the FGDs revealed that, farmers did not observe the drone pilot controlling the drone when watching the video of pesticides application. One farmer in Kplijine remarked, *“I saw a man fully dressed in personal protective equipment (PPEs) in the video but I did not know he was the one controlling the drone. I thought the drone was controlling itself”*. Other farmers also expressed same sentiments hence their similar opinion on the costs and benefits of the knowledge required to operate the drone and knapsack for control of FAW.

The columns in Table 34 on live application of pesticides show farmers perceived cost and benefits of drone and knapsack for control of FAW after watching live drone and knapsack application of pesticides in the field. In the same way, farmers generally perceived a significant difference ($t = 9.07$, $p = 0.00$) between the cost and benefits of using the drone (Composite mean = 5.96) and the knapsack (Composite mean = 5.00). Even though perceived significant difference [$(t = 5.83, p = 0.00)$ ($t = 6.08, p = 0.00$)] in costs and benefits of using drone over knapsack in terms of efficiency [(Mean = 7.46, S.D = 2.35), (Mean = 5.43, S.D = 2.57)] and performance [(Mean = 7.25, S.D = 2.53), (Mean = 5.20, S.D = 2.33)] respectively, they did not however perceive significant difference in the cost and benefits in the use of drone and knapsack in terms of ease of use [(Mean = 4.33, S.D = 3.69), (Mean = 4.92, S.D = 2.51), ($t = -1.52$,

$p = 0.00$], flexibility of manipulation [(Mean = 4.17, S.D = 3.64), (Mean = 4.72, S.D = 2.41), ($t = -3.24$, $p = 0.00$)] and the impact of climate on the usage of the equipment [(Mean = 5.20, S.D = 3.38), (Mean = 4.92, S.D = 2.03), ($t = 0.80$, $p = 0.00$)]. The results are in line with that of Faiçal et al. (2017) and Mogili and Deepak (2018) which revealed that poor landscape or terrain and erratic weather conditions such as unexpected changes of wind speed and direction affect the quality service provided by the spraying drone during spraying.

Farmers again after watching the live application of pesticides perceived significant difference in cost and benefits of using the knapsack [($t = -17.89$, $p = 0.00$), ($t = -17.83$, $p = 0.00$)] and the drone in terms of exertion of energy during spraying [(Mean = 8.01, S.D = 1.79), (Mean = 2.51, S.D = 1.95)] and the weight of the equipment on the sprayer [(Mean = 7.56, S.D = 1.51), (Mean = 2.71, S.D = 2.00)]. The results are not surprising as similar findings emerged from the FGDs especially among the older and female farmers. The data revealed one very obvious conclusion the weight and bulkiness of the knapsack and the energy exerted during spraying affect the control of FAW in the study area.

An old male farmer in Kukua remarked that, *“The knapsack is heavy and bulky, so carrying it at your back to spray a large farm area is very difficult because it draws a lot of energy from you, especially for those of us who are advanced in age. So this drone has come at a very good time for us.”* A female farmer in Loagri added that *“When it is filled with chemicals, the knapsack is very heavy. Moreover, you have to walk throughout the farm while pumping with one hand. All these activities demand a lot of energy which makes it difficult for some of us the old and female too. So the drone will solve all these problems for us.”* To buttress the point on the large farm sizes and the difficulty

of acquiring labour to apply chemicals to control the FAW, one farmer in Kpalsogu indicated that, *“I have a large farm (20 acres) and so using a knapsack to control the FAW takes a lot of labour and time. These days the labour is not even available, but the way I see the drone working, as it can spray the pesticides to control the FAW in a very short time, it relieve us of our burden.”*

The results mirror that of Sinha et al. (2018) which revealed that fatigue is one of the challenges involved with the use of the knapsack sprayer by farmers. The operator of the equipment may find it difficult maintaining continuous pressure on the pump due to stress and fatigue and begins to experience pain on the clavicle region, to lower back, in the neck and thighs (Sinha et al., 2018). Dandge and Ingole (2017) noted that fatigue increases because the operator has to carry the equipment on the back and ensure continuous pumping during pesticides application (Ganehiarachchi, 2015). The spraying exercise is usually slow because the liquid has to have direct contact with the crops which increases the duration of the pesticides application, hence smallholder farmers cultivating limited farm areas (Faïçal et al., 2017).

It is worth noting that, the perception of the farmers on the costs and benefits of using the drone and knapsack in terms of the impact of climate on the usage of the equipment, its bulkiness, and affordability which were significant when the farmers watched the video of the pesticides application, were, however, not significant during the live application of pesticides. Indicating that farmers changed their opinion but the change in opinion was not significant. On the other hand, two variables which were significant during both the video and live application of pesticides in favour of the drone over the

knapsack were spillage of pesticides during application and risk of the sprayer coming into contact with the chemicals. The FGD data revealed the same theme of safety of the sprayer and the environment when using the drone.

The farmers in Salanpang observed that, *“we can see that the sprayer does not come into contact with the chemicals during the spraying with the drone and so he is not afraid of spillage and getting drenched in the chemicals, as in the case of using the knapsack.”* In Nyankpala a farmer in support of the earlier statement indicated that, *“The drone poses no risk to the farmer at all because the farmer does not come into contact with the drone and the chemicals, but with the knapsack, the farmer will come into contact with the chemicals so there is always the possibility of risk of contamination which affects the health and safety of the farmer and the environment.”* The results reflect the suggestion of McAuliffe and Gray (2002) that inconsistent pressure applied during pesticides application influence the spray drift which worsen the operators' exposure to the pesticide causing health risks.

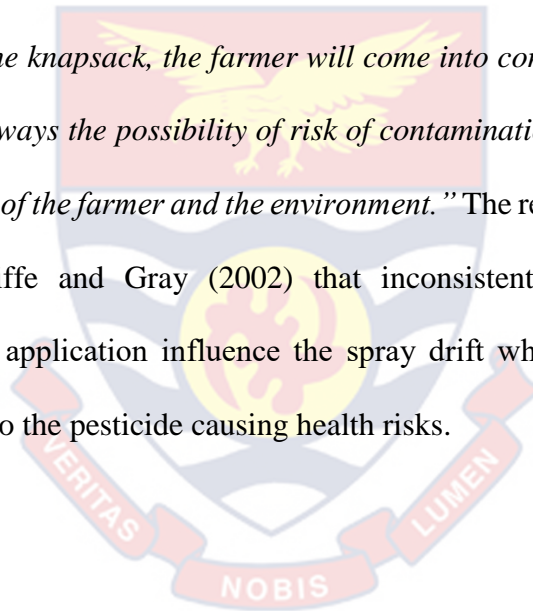


Table 34: Cost and Benefits of using Drone and Knapsack for pesticides application for control of FAW

Cost and Benefits	Video of Pesticides Application (N = 145)						Live Pesticides Application (N = 105)						
	Drone		Knapsack		T-value	P-value	Drone		Knapsack		T-value	P-value	
	Mean	S.D	Mean	S.D			Mean	S.D	Mean	S.D			
Efficiency of Equipment	8.48	2.22	4.32	2.39	14.12	0.00	Efficiency of Equipment	7.46	2.35	5.43	2.57	5.83	0.00
Performance of Equipment	8.37	2.30	4.40	2.38	13.99	0.00	Performance of Equipment	7.25	2.53	5.20	2.33	6.08	0.00
Ease of use of Equipment	8.33	2.61	3.94	2.36	14.52	0.00	Ease of use of Equipment	4.33	3.69	4.92	2.51	-1.52	0.13
Initial capital for acquisition	8.10	2.44	3.63	2.60	14.42	0.00	Initial capital for acquisition	5.90	3.43	3.90	2.22	5.16	0.00
FAW control consistency	7.95	2.53	5.26	3.04	7.96	0.00	FAW control consistency	5.55	3.63	6.53	2.86	-2.02	0.05
Flexibility of operation	7.88	2.61	4.41	2.46	10.28	0.00	Flexibility of operation	4.17	3.64	4.72	2.41	-1.38	0.17
Meet farmers' needs consistently	7.65	2.71	5.41	2.94	6.41	0.00	Meet farmers' needs consistently	5.16	3.50	6.72	2.91	-3.24	0.00
Reliability of the equipment	7.08	2.95	4.90	2.69	5.35	0.00	Reliability of the equipment	2.94	2.40	5.82	2.38	-8.23	0.00
Cost of pesticides application services	6.88	2.91	4.87	2.85	5.37	0.00	Cost of pesticides application services	6.03	2.47	4.91	3.02	2.40	0.02

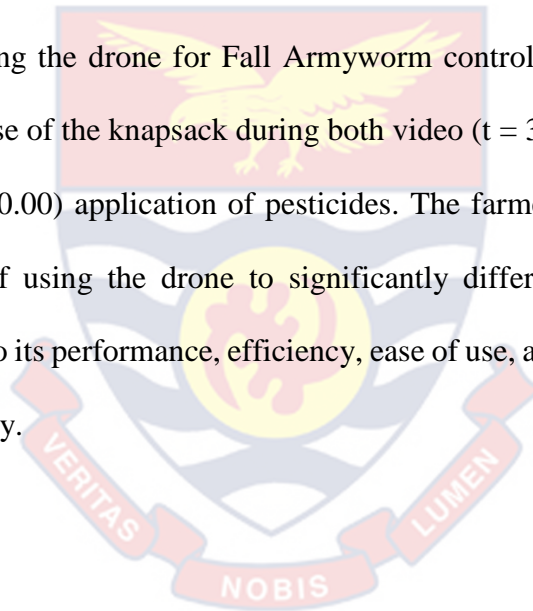
Cost of maintenance	6.56	2.81	4.81	2.60	4.60	0.00	Cost of maintenance	6.94	2.29	3.90	2.18	8.20	0.00
Skills needed to operate equipment	6.21	3.31	4.71	2.95	3.28	0.00	Skills needed to operate equipment	2.72	2.39	4.35	2.16	-7.21	0.00
Knowledge for operating equipment	5.90	3.23	5.17	3.07	1.62	0.11	Knowledge for operating equipment	7.00	2.61	4.62	2.24	6.33	0.00
Impact of climate on equipment (wind & rain)	4.92	3.16	5.86	2.74	-2.35	0.02	Impact of climate on equipment (wind & rain)	5.20	3.38	4.92	2.03	0.80	0.43
Bulkiness of the equipment	4.77	3.07	6.53	3.08	-4.03	0.00	Bulkiness of the equipment	5.20	2.57	5.68	2.63	-1.08	0.28
Landscape/terrain of the fields	4.75	2.89	5.70	2.83	-2.56	0.01	Landscape/terrain of the fields	6.78	2.48	5.08	2.45	5.34	0.00
Affordability of the technology	4.41	2.98	7.16	2.97	-6.34	0.00	Affordability of the technology	6.76	2.73	7.09	2.62	-0.94	0.35
Duration of pesticides application	4.37	3.14	7.61	2.77	-7.66	0.00	Duration of pesticides application	2.94	2.44	7.88	1.87	-13.10	0.00
Quantity of pesticides used	4.12	2.90	6.68	2.53	-7.09	0.00	Quantity of pesticides used	3.32	2.24	6.01	2.73	-8.58	0.00
Drift during application	3.97	3.11	6.59	2.67	-6.48	0.00	Drift during application	3.16	2.26	6.28	2.67	-12.16	0.00

Availability of labour to use equipment	3.55	2.77	7.14	2.85	-8.83	0.00	Availability of labour to use equipment	5.24	3.43	6.82	2.58	-4.79	0.00
Availability of support systems to use the technology	3.49	2.55	6.94	3.06	-8.89	0.00	Availability of support systems to use the technology	7.39	2.19	6.32	2.63	3.24	0.00
Safety risk of the sprayer	3.40	2.89	8.02	2.26	-12.37	0.00	Safety risk of the sprayer	5.85	3.63	7.60	1.94	-4.42	0.00
Spillage of pesticides during spraying	3.32	2.73	7.63	2.16	-12.63	0.00	Spillage of pesticides during spraying	3.00	2.29	6.41	2.48	-10.80	0.00
Exertion of energy during application	3.15	2.41	8.59	1.89	-17.99	0.00	Exertion of energy during application	2.51	1.95	8.01	1.79	-17.89	0.00
Effect of weight of the equipment on sprayer	2.99	2.43	8.32	1.81	-18.74	0.00	Effect of weight of the equipment on sprayer	2.71	2.00	7.56	1.51	-17.83	0.00
Availability of the equipment	2.77	2.44	8.58	2.19	-18.78	0.00	Availability of the equipment	4.50	3.54	8.20	1.65	-10.11	0.00
Composite mean	6.06		5.51		3.91	0.00	Composite mean	5.96		5.00		9.07	0.00

Source: Field data, Asante (2020). Mean were calculated from a scale of 1 = Very low to 10 = Very high

Chapter Summary

The chapter presented the results of objective three which compared the perception of the farmers on the demerits and merits of using the drone and knapsack sprayers to control of FAW in the study area. The adopted 26 costs and benefits variables were identified and used. Primary data was collected during video and live drone application of pesticides in the field. Data was analyzed using means, standard deviations and paired samples t-test to compare farmers' opinion of the demerits and merits of using drone and knapsack to control FAW. The results showed that farmers perceived the costs and benefits of accepting the drone for Fall Armyworm control to be significantly higher than the use of the knapsack during both video ($t = 3.91, p = 0.00$) and live ($t = 9.07, p = 0.00$) application of pesticides. The farmers observed the costs and benefits of using the drone to significantly different from the knapsack in relations to its performance, efficiency, ease of use, and Fall Armyworm control consistency.



CHAPTER EIGHT

BEHAVIOURAL INTENTION OF MAIZE FARMERS TO ADOPT DRONE TECHNOLOGY FOR THE CONTROL OF FAW

Introduction

Chapter Eight presents results and discusses objective four of the study which sought to examine the intention, desire, tendency or the propensity of maize farmers to adopt drone spraying services for Fall Armyworm control.

Evaluation of the Structural Model

After all the reflective measurement model criteria have been met, which provided evidence for the reliability and validity of the model, the next step was to assess the PLS-SEM results of the structural model of the intention, desire, tendency or the propensity of maize farmers to adopt drone spraying services for Fall Armyworm control. The structural model was assessed using the following standard criteria; structural model collinearity issues, coefficient of determination (R^2), f^2 effect size, the predictive relevance Q^2 , q^2 effective size and the statistical significance and relevance of the path coefficients (Hair, Risher, et al., 2019; Hair et al., 2017). Additionally, the out-of-sample predictive power of the model was assessed using PLSpredict procedure (Shmueli et al., 2016, 2019).

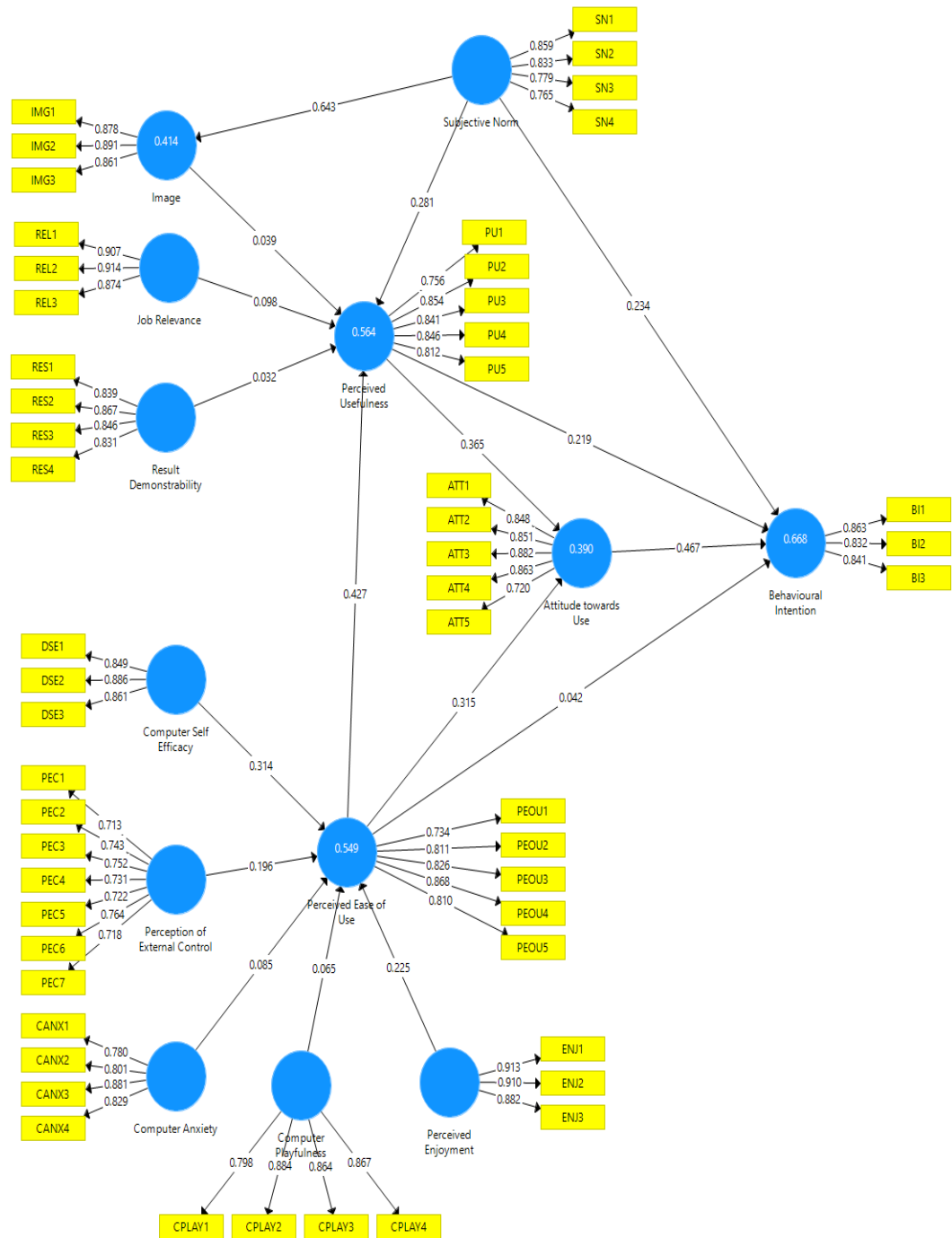


Figure 12: Estimated technology acceptance model (TAM 3) before variables were deleted.

Source: PLS-SEM Analysis, Asante (2020)

The Coefficient of Determination (R^2) of Behavioural Intention and Related Variables

The coefficient of determination (R^2) of all the dependent variables were computered as the degree of the variance defined in each of the constructs which represented the explanatory power of the model (Shmueli & Koppius, 2011). Rigdon (2012) indicated that R^2 is the in-sample predictive power of the structural equation model, thus as rule of thumb, R^2 values of 0.75, 0.50 and 0.25 are regarded as substantial, moderate and weak respectively (Hair et al., 2011). According to Hair, Risher, et al. (2019), R^2 should be interpreted based on the context of the current study, compared with results from previous research and models of similar complexity. The in-sample predictive power of the acceptance drone technology for applying pesticides for the control of FAW was done by evaluating the explained variance (R^2) and adjusted (R^2) for the dependent variables behavioural intention (BI), attitude towards use (ATT), PEOU, PU and image (IMG). Results of the PLS-SEM as depicted in Table 35 shows that the R^2 and adjusted R^2 values of the model range between 0.376, 0.372 and 0.674, 0.665 respectively, indicating that the model has high predictive power and relevant for explaining the variance in the dependent constructs in the model.

The results of the PLS-SEM as shown in Table 35 showed that, four variables (ATT, PU, PEOU, and SN) moderately predicted 67.4 percent of the variance in the intention, desire, tendency or the propensity of maize farmers to adopt drone spraying services for Fall Armyworm control (R^2 : BI = 0.674). The *Adjusted R2* = 0.665 is higher than that of Venkatesh and Bala (2008) which revealed an average prediction of between 45 percent of the variance in

behavioural intention. The higher R^2 for behavioural intention recorded in this study is as a result of the inclusion attitude towards use. Hair, Risher, et al. (2019) posited that, R^2 is a function of the number of predictors associated with the dependent constructs, hence, the higher the number of predictors, the higher the R^2 . The R^2 (BI: $R^2 = 0.674$) value recorded in this study is, however, less than the 0.90, which according to Hair, Risher, et al. (2019) in the context of models predicting attitudes, perceptions and intentions may indicate overfit.

Amin et al. (2015) and Al-gahtani (2016) examined behavioural intention of customers to use mobile wallet and e-learning acceptance and assimilation and revealed lower R^2 values for behavioural intention of $R^2 = 0.400$ and $R^2 = 0.420$ respectively. The results of this study mirror the findings of Shukla and Sharma (2018) which reported that, PU and ATT compositely explained 50 percent of the variance in behavioural intention of grocery shop customers to adopt mobile technology for shopping. Contrary to this study is the findings of Gbongli et al. (2019) which concluded that, attitude explained less than 14.6 percent of the variance in the behavioural intention of mobile phone subscribers to adopt mobile money services in the West African country of Togo. The four determinants of behavioural intention in this study: 'PU', 'PEOU', 'ATT' and 'SN', indicate that when the maize farmers perceive the drone to be useful and easy to use, they develop a positive attitude towards the use of the technology, which will affect their intention to use the drone for spraying pesticides for the control FAW (Venkatesh & Bala, 2008; Venkatesh & Davis, 2000) provided most of the people who are important to them think they should use the technology (Davis et al., 1989; Fishbein & Ajzen, 1975).

Table 35 also presents the coefficient of determination of the attitude of the maize farmers towards the use of drone technology for spraying pesticides for control of FAW, was predicted by perceived usefulness and perceived ease of use (ATT: $R^2 = 0.440$). The results align with the findings of Amin et al. (2015) and Gbongli et al. (2019) which concluded that PU and PEOU of use jointly accounted for 32 percent and 50 percent respectively of the variance in the attitude towards use of technology. Riskinanto et al. (2017) and Shukla & Sharma (2018) in different research projects revealed higher effect of PU and PEOU on attitude towards the use of mobile technology for shopping among customers. Riskinanto et al. (2017) and Shukla and Sharma (2018) revealed that perceive usefulness and ease of use both explained 65 percent and 82 percent respectively of the variance in attitude towards use of technology. The results mean that when the maize farmers perceive the drone to be useful and ease to use, their attitude towards the use of drone technology for spraying pesticides for control of FAW would greatly improve.

Table 35 presents four independent variables namely: 'PEOU', 'IMG', 'SN' and 'RES' moderately accounted for 57.0 percent of the variance in perceived usefulness of drone technology for the application of pesticides for control of FAW (PU: $R^2 = 0.570$). The *adjusted R²* (0.558) is consistent with the findings of Venkatesh and Bala (2008) concluded that perceived ease of use, subjective norms, image, job relevance, output quality and demonstability jointly explained an average of 60 percent of variance in perceived usefulness. It is worth noting that job relevance did not however pass the HTMT discriminant validity criteria, hence was deleted from the model.

The four independent variables of perceived usefulness specifically: ‘perceived ease of use’, ‘subjective norm’, ‘image’ and ‘result demonstrability’ had a stronger effect of perceived usefulness (*Adjusted R*² = 0.558) compared with the findings of Al-gahtani (2016), which reported that PEOU, SN, IMG, REL and OQ compositely explained 42.4 percent of the variation in perceived usefulness (*R*² = 0.424) of adopting online learning management systems among college students in Saudi Arabia. Table 35 also shows that subjective norm accounted for the 37.6 percent of the variations of the image of the farmers in the communities where the study was carried out (IMG: *R*² = 0.376). Similar findings were re-counted by Venkatesh and Bala (2008) and Al-gahtani (2016) who revealed a strong impact of SN and IMG. The determinants of PU implies that the perception of the maize farmers on the usefulness of drone spraying services for Fall Armyworm control is greatly influenced by their perception of the ease of use of the technology and the belief that the people who are important to them think they should use the technology (Davis et al., 1989; Fishbein & Ajzen, 1975) because the technology is likely to enhance their social status in the community due to the tangible, observable and communicable results of adopting the drone services for control of FAW (Moore & Benbasat, 1991).

As shown in Table 35, four independent variables of perceived ease of use namely: ‘anxiety’, ‘playfulness’, ‘perception of external control’ and ‘perceived enjoyment’ predicted 49.0 percent of variance in perceived ease of use (PEOU: *R*² = 0.490). The results are consistent study is the findings of Venkatesh and Bala (2008) which concluded that self-efficacy, perception of external control, anxiety, playfulness and perceived enjoyment explained an

average of 48 percent of the variations in perceived ease of use (PEOU: *Adjusted* $R^2 = 0.476$). Similar findings were also reported by Al-gahtani (2016) which revealed that the anchor variables collectively accounted for 45 percent of the variations within PEOU ($R^2 = 0.450$). The effect of self-efficacy in this study was however removed from the model because it did not meet the HTMT discriminant validity criteria. The results imply that, the belief of the maize farmers that organizational and technical resources exist to support the use of the drone (Venkatesh et al., 2003), the extent to which the activity of using the drone for spraying pesticide is perceived to be enjoyable, due to the farmers' cognitive spontaneity in use of the drone and little apprehension, or even fear with the possibility of using drone (Venkatesh, 2000), significantly explained the variance in the perception of the farmers about the ease of use of the drone technology services for spraying pesticides for control of FAW.

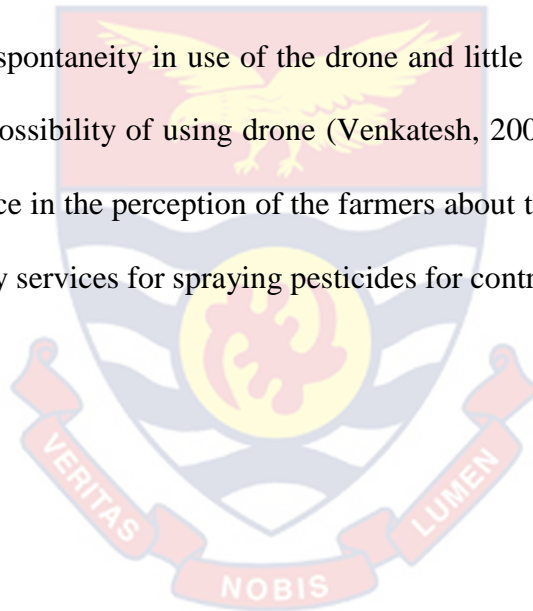


Table 35: Coefficient of determination (R^2), predictive sample reuse technique (Q^2) and f^2 and q^2 effect sizes

Dependent Constructs	R^2	Adjusted R^2	Q^2	Relationships	f^2	Decision	q^2	Decision
BI	0.674	0.665	0.437	ATT -> BI	0.296	Medium	0.092	Small
				PEOU -> BI	0.020	Small	0.002	No effect
				PU -> BI	0.080	Small	0.028	Small
				SN -> BI	0.050	Small	0.009	No effect
ATT	0.440	0.432	0.300	PEOU -> ATT	0.107	Small	0.053	Small
				PU -> ATT	0.141	Small	0.064	Small
PEOU	0.490	0.476	0.251	CANX -> PEOU	0.023	Small	0.004	No effect
				CPLAY -> PEOU	0.00	No effect	0	No effect
				ENJ -> PEOU	0.159	Medium	0.057	Small
				PEC -> PEOU	0.058	Small	0.013	No effect
				IMG -> PU	0.010	No effect	-0.014	No effect
PU	0.570	0.558	0.355	PEOU -> PU	0.288	Medium	0.126	Small
				RES -> PU	0.000	No effect	-0.008	No effect
				SN -> PU	0.127	Small	0.047	Small
				SN -> IMG	0.604	Large	0.274	Medium
IMG	0.376	0.372	0.274	SN -> IMG	0.604	Large	0.274	Medium

Source: PLS-SEM Data Analysis, Asante (2020).

The f^2 effect sizes of the independent variables on the dependent variables in the model

The f^2 effect size was computed to assess the change in the R^2 value when a specific independent variable is removed from the model to evaluate its substantive impact on the dependent construct (Hair et al., 2017). The standard criteria for assessing the f^2 effect size are values greater than 0.02, 0.15 and 0.35 which indicate small, medium and large effective based on the Cohen (1988) effect size criteria. Table 35 shows that the intention as the main explained variable is predicted by four independent variables: 'attitude towards use', 'PU' 'PEOU', and 'SN'. Based on Cohen's (1988) standard criteria, attitude towards use of drone technology services for control of FAW had medium effect ($f^2 = 0.296$) of intention whilst perceived usefulness ($f^2 = 0.020$), ease of use ($f^2 = 0.080$), and subjective norm ($f^2 = 0.050$) had small effect on intention respectively. The results are aligned with the findings of Gbongli et al. (2019) who also reported that attitude was the strongest predictor of behavioural intention of mobile phone users to adopt mobile money services in the Republic of Togo.

The results, however, contradicted the findings of Venkatesh and Bala (2008) which found perceived usefulness as the strongest predictor of behavioural intention. It is worth highlighting that, the effect of attitude which was part of the novel TAM posited by Davis (1989) was omitted from the extended TAM by Venkatesh and Bala (2008). This was because Venkatesh and Bala (2008) found attitude and intention as similar constructs hence, the reason for omitting attitude from the extended technology acceptance model TAM 3. On the other hand, in this study, the two constructs passed the HTMT

discriminant validity criteria, therefore, similarity of the two variables could not be assumed. It can be deduced that in a model where attitude is omitted, perceived usefulness would be the strongest predictor of behavioural intention as reported by (Al-gahtani, 2016). Moreover, Amin et al. (2015), SevİM et al. (2017) and Shukla and Sharma (2018) reported that attitude and usefulness are the strongest predictors of behavioural intention with the two constructs accounting for the strongest effect on intention of individuals to use technology. The results indicate that, when maize farmers find the drone technology services to be useful for spraying pesticides for control of FAW, they develop favourable attitude towards its usage, that enhances their intention to adopt the technology on the maize fields.

The f^2 effect size of perceived usefulness and ease of use on the attitude (second dependent variable) of the maize farmers towards the use of drone technology spraying pesticides for control of FAW indicated that both perceived usefulness ($f^2 = 0.141$) and ease of use ($f^2 = 0.107$) had small effect on attitude while usefulness had a substantial small effect compared to ease of use (Table 35). The results are consistent with the findings of earlier studies on adoption of technologies applying the Technology Acceptance Model (Al-gahtani, 2016; Davis, 1989; Gbongli et al., 2019; Riskinanto et al., 2017; SevİM et al., 2017; Shukla & Sharma, 2018; Venkatesh & Davis, 2000). Amin et al. (2015) found that perceived usefulness has a motivational influence on an individual to develop positive attitude towards the use of technology. Lai (2017) concluded that perceived usefulness is the strongest determinant of user attitude toward the use of technologies.

Table 35 shows that PEOU had medium effect ($f^2 = 0.288$) on PU whilst subjective norm had small effect ($f^2 = 0.127$). On the contrary, image ($f^2 = 0.010$) and result demonstrability ($f^2 = 0$) had no influence on PU, whilst subjective norm ($f^2 = 0.604$) had large effect on the image of the farmers. Confirmed by this current study is the dominant effect of PEOU on PU as indicated by Venkatesh and Bala (2008). Fosso Wamba and Trinchera (2014) reported similar findings by concluding that PEOU independently accounted for 33 percent of the impact on PU. Also confirmed by this study was the small and substantial impact of SN on usefulness and image (Venkatesh & Bala, 2008). The results are consistent with the findings of Al-gahtani (2016) which found that result demonstrability was the only construct which had no influence on PU of adopting online management systems among college students in Saudi Arabia. The result implies that the maize farmers did not perceive the results of using the drone technology services for spraying pesticides for control of FAW were concrete, noticeable and transmissible (Moore & Benbasat, 1991). Also, the influence of job relevance on PU did not reflect the findings of Al-gahtani (2016).

Again, Table 35 shows that anxiety ($f^2 = 0.023$) and perception of external control ($f^2 = 0.058$) had small effect on perceived ease of use whilst perceived enjoyment ($f^2 = 0.159$) had medium effect. On the other hand playfulness ($f^2 = 0.00$) had no effect on perceived ease of use. The results of perceived enjoyment having the strongest effect on perceived ease of use reflect the findings of Sevím et al. (2017) who found that perceived enjoyment independently predicted 31 percent of the effect on PEOU. The no effect of playfulness on PEOU was consistent with the findings of Al-gahtani (2016).

The results indicated the absence of cognitive spontaneity among the maize farmers to utilize drone technology for spraying pesticides for control of FAW in the study area (Webster & Martocchio, 1992).

Venkatesh and Bala (2008) and Al-gahtani (2016) posited that PEC exhibited the strongest effect among the anchor variables on PEOU of technologies. The results however, contradicted the findings of Venkatesh and Bala (2008) and Al-gahtani (2016) which concluded that PEC is the strongest determinant of PEOU. The finding indicated that the maize farmers perceived there is insufficient organizational and technical resources in the research area to support the deployment of drone services for spraying insecticides for Fall Armyworm control (Venkatesh et al., 2003). This finding is not surprising, considering that drone technology services providers are not at this time located in the northern part of the country.

The Magnitude of the Predictive Accuracy of the Dependent Variables in the Model: (Blindfolding and Predictive Relevance Q^2)

The magnitude of the predictive accuracy of the dependent variables was examined using the Stone-Geisser's Q^2 values to estimate the predictive relevance in the model (Geisser, 1974; Stone, 1974). The Q^2 values were obtained by applying the blindfolding procedure for a specific omission distance D (Hair et al., 2017). The PLS-SEM algorithm of Q^2 combined features of out-of-sample estimation and in-sample explanatory power as input (Shmueli et al., 2016) by applying the blindfolding technique to calculate the data points that were removed for all constructs in the model (Hair, Risher, et al., 2019). Hence, the small variations between the projected and the original values translated

into a higher Q^2 value, thereby indicating a higher predictive accuracy of the model (Hair et al., 2017).

The results of Q^2 greater than zero indicated that the independent variables had predictive relevance for the specific dependent variables they were linked to (Hair et al., 2011; Hair et al., 2014). As a rule of thumb Hair, Risher, et al. (2019) posited that, Q^2 values greater than zero, 0.25 and 0.50 indicated small, medium and large predictive relevance of the PLS-path model respectively. Applying the default D value of 7, the blindfolding algorithms of the PLS-path model was estimated for all the five dependent variables presented the PLS-path model's Q^2 values for the study.

Table 35 shows that the respective independent variables had medium predictive relevance on all the five dependent variables. Perceived usefulness, ease of use, attitude and subjective norm had the highest predictive relevance on behavioural intention ($Q^2 = 0.437$). Perceived usefulness ($Q^2 = 0.355$) had the second highest predictive relevance by its independent variables followed by attitude towards use ($Q^2 = 0.300$), image ($Q^2 = 0.274$) and ease of use ($Q^2 = 0.251$). The results indicated that the PLS-path model exhibited good predictive relevance and accurately predicted the data not used in the model estimation (Hair Jr et al., 2017).

The Relative Impact of the Predictive Relevance of the Independent variables in the Model (Assessing q^2 Effect Size)

Like the f^2 effect sizes, the q^2 effect sizes were manually computed and interpreted from blindfolding estimations (Hair, Risher, et al., 2019) using the following formula: $q^2 = Q^2_{\text{included}} - Q^2_{\text{excluded}}$ divided by $1 - Q^2_{\text{included}}$ (Hair et al., 2017). The Q^2_{excluded} are values obtained from the model re-estimation after

omitting a specific independent variable of a dependent variable is the q^2 effect size of the independent on the dependent variable (Hair, Risher, et al., 2019). Table 35 shows PEOU ($q^2 = 0.002$) and SN ($q^2 = 0.009$) had no effect on the predictive relevance of behavioural intention in the model whilst both perceived usefulness ($q^2 = 0.028$) and attitude towards use ($q^2 = 0.092$) had small effects on intention. The results imply that both perceived usefulness and attitude support the predictive relevance of the intention, desire, tendency or propensity of the farmer to accept drone spraying services for Fall Armyworm control.

The effect of PU ($q^2 = 0.064$) and PEOU ($q^2 = 0.053$) on the predictive relevance of attitude towards use of drone technology services for control of FAW was small with usefulness having the highest effect. Both image ($q^2 = -0.014$) and result demonstrability ($q^2 = -0.008$) had no effects on the predictive relevance of the dependent variable, perceived usefulness. On the other hand, perceived ease of use ($q^2 = 0.126$) and subject norm ($q^2 = 0.047$) had small effect on PU, PEOU had the highest effect. The impact of SN ($q^2 = 0.274$) on IMG was moderate. Also, anxiety ($q^2 = 0.004$), playfulness ($q^2 = 0$) and perception of external control ($q^2 = 0.013$) all had no effect on the predictive relevance of perceived ease of use in the model, however, the effect of perceived enjoyment ($q^2 = 0.057$) on perceived ease of use was small. In brief, the results of R^2 , Q^2 , f^2 and q^2 analysis indicated that the findings of the PLS path model were relatively vigorous.

Model Fitness Index

Model fit is not emphasized in PLS-SEM (Hair Jr et al., 2017). However, by accepting this criterion as sufficient fit criterion, it prioritizes maximizing the target constructs' explained variance (Schloderer et al., 2014). The global

Goodness of Fit index (GOF) was employed as an index for the comprehensive model fit in the PLS-SEM to assess whether the model adequately described the empirical data (Tenenhaus et al., 2005).

A good model fit indicates how sparse and realistic a model is (Henseler et al., 2016). The geometric mean value of average variance extracted (AVE values) and the average R^2 value were used to calculate the GOF(s). The calculated results for $GOF = 0.545$ is based on the formula presented by Tenenhaus et al. (2005) and the recommendation introduced by Wetzels, Odekerken-Schröder and van Oppen (2009) to qualify the effect of magnitude of the GOF (See Table 47, Appendix M). The goodness of fit index is large enough to support the global model validity, which leads to the conclusion that the model is valid (Tenenhaus et al., 2005).

Assessing the Direct Relationships and Path Coefficients (Hypothesis Testing)

In evaluating the statistical significance of the path model's coefficients, the t-statistics was calculated utilizing the "Bootstrapping Procedure". Bootstrap is a nonparametric approach for assessing the accuracy of the PLS estimate (Chin, 1998). The bootstrap sample was set to 5000 at 95% confidence interval as suggested by (Hair et al., 2017) before running the "bootstrapping procedure" in Smart PLS software version 3.3.2 (Ringle et al., 2015). The number of observations was 150 which was the exact sample size of the study (Hair et al., 2017). The estimated path coefficients and t-statistics are shown in the columns three and five respectively of the Table 36 show that, two of the direct relationships of behavioural intention were significant [positive significant relationship between PU and ATT and BI ($\beta = 0.253, p < 0.05; \beta =$

0.424, $p < 0.001$)] while two were not. The result implies that, as the maize farmers perceived the drone for controlling FAW to be useful, they developed positive attitude towards its use, which strongly influenced their intention to use the technology. The results are consistent with the conclusions of Venkatesh and Bala (2008) and Al-gahtani (2016). Amin et al. (2015), SevİM et al., (2017), Shukla and Sharma (2018) and Gbongli et al. (2019) that there is a strong positive relationship between PU and ATT and BI. Therefore, hypothesis H_{06a} and H_{06b} were supported by the path model.

The relationships between PEOU → BI and SN → BI were not significant ($\beta = 0.116, p > 0.05$; $\beta = 0.172, p > 0.05$) (Table 36). The non-significant relationship between PEOU on BI mirrors the findings of Venkatesh and Bala (2008) and Amin et al. (2015). Al-gahtani (2016) on the other hand found there was a positive relationship between PEOU and subjective norm on BI. The results imply that when farmers perceived that utilizing the drone for control of FAW would not be free from stress (Davis et al., 1989), because important relatives think they should not use the technology, hence hypothesis H_{06c} and H_{06d} were not supported.

Table 36 showed that PU and PEOU had strong positive relationships with ATT ($\beta = 0.386, p < 0.001$; $\beta = 0.336, p < 0.001$). Prior research reported strong significant relationships between PU → ATT and PEOU → ATT (Amin et al., 2015; Gbongli et al., 2019; Riskinanto et al., 2017; SevİM et al., 2017; Shukla & Sharma, 2018). The findings indicated that the farmers found the use of drone for control of FAW to be useful and easy to use which enabled them to develop a positive attitude towards the use of the technology. Hence, both hypotheses H_{06e} and H_{06f} were supported. Furthermore, the results revealed

that whiles social influence variable SN and the cognitive instrumental process construct PEOU exhibited strong positive significant relationship on PU ($\beta = 0.331, p < 0.001$; $\beta = 0.456, p < 0.001$) with PEOU showing the strongest influence, social influence variable IMG ($\beta = 0.088, p > 0.05$) and the rest of the cognitive instrumental process constructs, job relevance (not computed) and result demonstrability ($\beta = 0.001, p > 0.05$) showed no significant relationship with PU (Table 36).

The results of the positive relationship between SN and PEOU and PU was consistent with the conclusions of Venkatesh and Bala (2008) and Al-gahtani (2016). The results also reflect the findings of Al-gahtani (2016) which found that result demonstrability (RES) had no significant relationship with perceived usefulness (PU). On the other hand, the relationship between IMG and PU was not in line with the findings of Al-gahtani (2016), which revealed a significant relationship between IMG and PU. Prior research also reported strong positive relationship between perceived ease of use and perceived usefulness (Gbongli et al., 2019; SevİM et al., 2017; Shukla & Sharma, 2018). The results also indicated that subjective norm (SN) exhibited strong positive influence on IMG, which is in line with the findings of Venkatesh and Bala (2008) and Al-gahtani (2016). The results implied that when the farmers perceived that the use of the drone for control of FAW was free from effort and the people who were important to them thought they should adopt the technology (Davis et al., 1989; Fishbein & Ajzen, 1975), their perception of the usefulness of the drone for control of the FAW improved (Davis, 1989). Therefore, hypothesis H_{07a}, H_{07f} and H_{07h} were supported whilst H_{07b}, H_{07c} and H_{07e} were not supported.

Finally, all anchor variables exhibited no significant relationship with PEOU except perception of external control PEC ($\beta = 0.283, p < 0.01$) and perceived enjoyment ENJ ($\beta = 0.371, p < 0.01$) as the adjustment variables which showed significant relationships as determining factor of PEOU (Table 36). The results of the significant relationship between PEC and PEOU mirrored findings of Venkatesh (2000) and Venkatesh and Bala (2008). On the contrary, the results were not in line with that of Gbongli et al. (2019) which reported of positive relationships between perceived ease of use and anxiety and self efficacy. The findings were, however, in line with that of SevİM et al. (2017) which found a strong relationship between perceived ease of use and perceived enjoyment, but in contradiction with the findings of (Venkatesh & Bala, 2008). Result implied that when the maize farmers believed that organizational and technical resources existed to support the use of the drone for control of FAW (Venkatesh et al., 2003) and perceive the activity of using the drone for spraying to be enjoyable (Venkatesh, 2000), their perception of the ease of use of the technology for spraying pesticides for control of FAW improved. Therefore, hypotheses H₀8b and H₀8e were supported whilst H₀8a, H₀8c and H₀8d were not supported by the path model.

Table 36: Direct Relationships and Path Coefficients (Hypothesis Testing)

Hypothesis	Relationships	Path Coefficient	S.E	T-Values	2.5% CI LL	97.5% CI UL	Decision
H ₀ 6a	PU -> BI	0.253	0.125	2.023*	-0.012	0.474	Supported
H ₀ 6b	ATT -> BI	0.424	0.082	5.159***	0.256	0.575	Supported
H ₀ 6c	PEOU -> BI	0.116	0.118	0.982	-0.126	0.326	Not Supported
H ₀ 6d	SN -> BI	0.172	0.092	1.866	-0.018	0.339	Not Supported
H ₀ 6e	PU -> ATT	0.386	0.128	3.008***	0.126	0.618	Supported
H ₀ 6f	PEOU -> ATT	0.336	0.123	2.735***	0.107	0.575	Supported
H ₀ 7a	SN -> PU	0.331	0.133	2.500**	0.057	0.56	Supported
H ₀ 7b	IMG -> PU	0.088	0.11	0.799	-0.141	0.282	Not Supported
H ₀ 7d	REL -> PU						Not Supported
H ₀ 7e	RES -> PU	0.001	0.121	0.009	-0.244	0.224	Not Supported
H ₀ 7f	PEOU -> PU	0.456	0.115	3.979***	0.236	0.681	Supported
H ₀ 7h	SN -> IMG	0.614	0.083	7.430***	0.429	0.756	Supported
H ₀ 8a	SE -> PEOU						Not Supported
H ₀ 8b	PEC -> PEOU	0.283	0.116	2.433**	0.045	0.508	Supported
H ₀ 8c	ANX -> PEOU	0.150	0.113	1.323	-0.091	0.348	Not Supported
H ₀ 8d	PLAY -> PEOU	0.007	0.105	0.066	-0.184	0.241	Not Supported
H ₀ 8e	ENJ -> PEOU	0.371	0.121	3.064**	0.116	0.592	Supported

Source: PLS-SEM Data Analysis, Asante (2020). * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$.

Indirect Relationships and Mediating Effect of variables in the Model

The results presented in Table 37 show that only three indirect relationships were exhibited by the latent constructs in the model. There was positive statistically significant indirect (mediating) effect of attitude in the relationship between PEOU \rightarrow ATT \rightarrow BI ($\beta = 0.155, p < 0.05$) and PU \rightarrow ATT \rightarrow BI ($\beta = 0.160, p < 0.01$), indicating complementary mediation effect of attitude regarding the relationship between perceived ease of use and usefulness and behavioural intention. The results suggested that the perception of the maize farmers about the usefulness and ease of use of the drone on their intention to adopt the spraying services for Fall Armyworm control was made stronger by their attitude towards the utilization of the innovation. Hence hypotheses H_{06g} and H_{06h} were supported.

The results also show that there was no mediating effect of perceived usefulness on the relationships between the social influence (SN \rightarrow PU \rightarrow BI: $\beta = 0.078, p > 0.05$; IMG \rightarrow PU \rightarrow BI: $\beta = 0.018, p > 0.05$) and cognitive instrumental (PEOU \rightarrow PU \rightarrow BI: $\beta = 0.115, p > 0.05$; RES \rightarrow PU \rightarrow BI: $\beta = 0.008, p < 0.05$) processes and behavioural intention. The mediating effect of social influence process, image on the indirect relationship between subjective norm and perceived usefulness was also not significant (SN \rightarrow IMG \rightarrow PU: $\beta = 0.043, p > 0.05$). The results contradicted the theory underpinning the extended technology acceptance model TAM 2. Venkatesh and Davis (2000) posited that, the effect of social influence and cognitive instrumental processes on behavioural intention were mediated by PU. The results of the path model do not support this theory therefore hypotheses H_{07c}, H_{07h}, H_{07i}, H_{07j} and H_{07k} were not supported by the model.

Table 37: Indirect Relationships (Hypothesis Testing)

Hypothesis	Relationships	Path Coefficients	S.E	T Values	2.50% LL	97.50% UP	Decision
H ₀ 6g	PEOU -> ATT -> BI	0.155	0.066	2.156*	0.039	0.29	Supported
H ₀ 6h	PU -> ATT -> BI	0.160	0.059	2.766**	0.059	0.295	Supported
H ₀ 7c	SN -> IMG -> PU	0.043	0.07	0.768	-0.096	0.176	Not Supported
H ₀ 7h	PEOU -> PU -> BI	0.115	0.066	1.733	0.006	0.27	Not Supported
H ₀ 7i	RES -> PU -> BI	0.008	0.035	0.008	-0.072	0.072	Not Supported
H ₀ 7j	SN -> PU -> BI	0.078	0.052	1.623	0.007	0.213	Not Supported
H ₀ 7k	IMG -> PU -> BI	0.018	0.032	0.698	-0.026	0.106	Not Supported
H ₀ 8f	ANX -> PEOU -> BI	0.015	0.026	0.68	-0.016	0.102	Not Supported
H ₀ 8g	PLAY -> PEOU -> BI	0.003	0.017	0.048	-0.032	0.04	Not Supported
H ₀ 8h	PEC -> PEOU -> BI	0.033	0.041	0.804	-0.027	0.141	Not Supported
H ₀ 8i	ENJ -> PEOU -> BI	0.031	0.044	0.986	-0.031	0.134	Not Supported
H ₀ 8j	ANX -> PEOU-> PU	0.078	0.063	1.085	-0.039	0.206	Supported
H ₀ 8k	PLAY-> PEOU-> PU	-0.001	0.049	0.064	-0.109	0.090	Supported
H ₀ 8l	PEC -> PEOU -> PU	0.131	0.060	2.152*	0.028	0.26	Not Supported
H ₀ 8m	ENJ -> PEOU -> PU	0.177	0.09	1.887	0.039	0.388	Supported

Source: PLS-SEM Data Analysis, Asante (2020). * = $p < 0.05$, ** = $p < 0.01$.

Furhermore, the mediating effect of perceived ease of use on its determinant (ANX->PEOU->BI: $\beta = 0.015, p > 0.05$; PLAY->PEOU->BI: $\beta = 0.003, p > 0.05$; PEC->PEOU->BI: $\beta = 0.003, p > 0.05$ and ENJ->PEOU->BI: $\beta = 0.031, p > 0.05$) and intention was not statistically significant (Table 37). The results contradicted the findings of Venkatesh (2000) and Venkatesh and Bala (2008) which stated that PEOU mediate the effect of the anchor and adjustment variables on intention. This finding suggested that the farmers' intention to adopt drone technology for spraying pesticides for the FAW control was not indirectly influenced by the determinants of perceived ease of use. Therefore, hypotheses H_{08f} to H_{08i} was not supported by path model.

Finally, Table 37 shows that the mediating impact of PEOU of its determinants on PU (ANX->PEOU->PU: $\beta = 0.078, p > 0.05$; PLAY->PEOU->PU: $\beta = -0.001, p > 0.05$ and ENJ->PEOU->PU: $\beta = 0.177, p > 0.05$) was not statistically significant except the perception of external control (PEC->PEOU->PU: $\beta = 0.131, p < 0.05$). The results were in line with the theory of technology acceptance as posited by Venkatesh (2000) and Venkatesh and Bala (2008) except perception of external control. The authors posited that, the drivers of PEOU would not significantly impact on perceived usefulness over and above the well known determinants of usefulness driven by the social influence and cognitive instrumental processes.

The finding means that apart from perception of external control, the perception of the maize farmers of the usefulness of the drone spraying services for Fall Armyworm control was not indirectly influenced by anxiety, playfulness and perceived enjoyment. Therefore, hypotheses H_{08j}, H_{08k} and H_{08m} were supported by the path model while H_{08l} was not supported. The

results with respect to the significant indirect effect of perceptions of external control on usefulness indicated that the maize farmers believed the organisational, and technical resources exist to support the adoption of drones for pesticides application for FAW control.

Modelling Moderating Effects of Experience and Voluntariness

Moderation denotes a condition in which the relationship between two constructs in the model is not constant but is subject to the values of a third variable known as a moderator (Hair et al., 2017). The effect of the moderator changes the magnitude or the direction of the relationship between the two constructs in the model (Hair et al., 2011; Hair et al., 2014). The moderators used are voluntariness and year of farming experience. The assessment of the moderator variables' measurement model indicated that the measures of voluntariness were both reliable and valid. The construct's indicator loadings was above 0.70, the convergent validity evaluation resulted in AVE above 0.50, supporting convergent validity of moderator voluntariness. Cronbach's alpha and composite reliability were above 0.70, indicating internal consistency. The HTMT ratio was evaluated for discriminant validity which produced a value which is less than 0.85. The results indicate discriminant validity. The moderator experience was a single item variable hence its measurement indicator were not assessed (Hair et al., 2017).

The results of the moderation presented in Table 38 showed that the two moderator variables had no significant impact on their respective relationships in the model. Voluntariness did no have significant moderating impact (VOL*SN -> BI: $\beta = 0.023$, $p > 0.05$) on the relationship between subjective norm on BI (Table 38). Also, the moderating effect of experience (EXP*SN ->

BI: $\beta = -0.066, p > 0.05$) on the relationship between subjective norm and BI was not significant. Again, experience did not have significant moderating effect on the association between subjective norm and PU (EXP*SN \rightarrow PU: $\beta = 0.002, p > 0.05$). Similar findings were found for experience and the relationship between PEOU and anxiety (EXP*CANX \rightarrow PEOU: $\beta = -0.002, p > 0.05$), playfulness (EXP*CPLAY \rightarrow PEOU: $\beta = 0.001, p > 0.05$), perceived enjoyment (EXP*ENJ \rightarrow PEOU: $\beta = 0.001, p > 0.05$) and behavioural intention (EXP*PEOU \rightarrow BI: $\beta = -0.001, p > 0.05$). The results contradicted the findings of Venkatesh and Bala (2008) which concluded that the moderating influence of both VOL and experience on the relationships posited in TAM 3.

However, there was moderating effect of years of farming experience on the relationship between PEOU and PU (EXP*PEOU \rightarrow PU). Experience has a positive interaction effect (PU: $\beta = 0.006$), whilst the modest influence of PEOU on PU is 0.456. Generally, the results suggest that the relationship between PEOU and PU is 0.456 for an average number of years of farming experience of 18.70 years of the maize farmers. For a standard unit increase in the number of years of experience of the farmers, the relationship between PEOU and usefulness increases by 0.462 (i.e., $0.456 + 0.006 = 0.462$). On the other hand, for lower years of farming experience, the relationship between PEOU and PU becomes $0.456 - 0.006 = 0.45$. Using the BCa bootstrapping analysis with 10,000 samples, two tailed testing yielded a p value of 0.05 with t value = 1.685 for the path linking the years of farming experience and perceived usefulness. Again, the 95 percent bias-corrected bootstrap confidence interval of the effect of years of farming experience is (0.001, 0.012) signifying that the confidence interval does not include zero, hence the conclusion made

that the effect is significant. The results imply that as the years of farming experience increases, the association between PEOU and PU increases and vice versa.

The results of experience which were measured as the years of farming experience of the maize farmers does not significantly moderate the relationships in the model. Therefore hypothesis $H_0(6i)$ which stated that the social influence process variable (VOL) will significantly moderate the influence of SN on behavioural intention (BI) to use drone technology for the control of FAW was rejected. Also, hypothesis $H_0(9)$ which indicated that years of farming experience (EXP) as a moderator in TAM3 will significantly moderate six intended paths in the model was rejected and the path between PEOU and PU accepted.

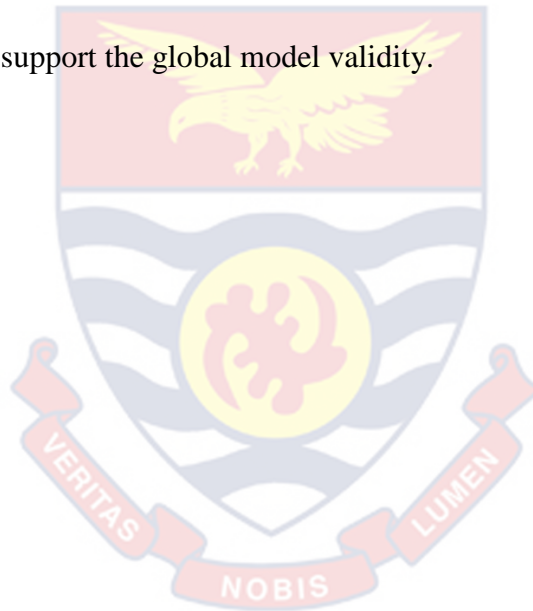
Table 38: Modeling Moderating Effects

Moderation Relationship	Path Coefficient	S.E	T Values	5.00%	95.00%	Decision
VOL*SN -> BI	0.023	0.017	1.356	-0.011	0.046	Not supported
EXP*SN -> BI	-0.066	0.051	1.247	-0.165	0.004	Not supported
EXP*SN -> PU	0.002	0.006	0.112	-0.009	0.010	Not supported
EXP*PEOU -> PU	0.006	0.004	1.685*	0.001	0.012	supported
EXP*CANX -> PEOU	-0.002	0.004	0.623	-0.010	0.003	Not supported
EXP*CPLAY -> PEOU	0.001	0.004	0.043	-0.006	0.006	Not supported
EXP*ENJ -> PEOU	0.004	0.007	0.657	-0.011	0.012	Not supported
EXP*PEOU -> BI	-0.001	0.004	0.370	-0.008	0.005	Not supported

Source: PLS-SEM Data Analysis, Asante (2020). * = $p < 0.05$

drone spraying services for Fall Armyworm control. The effect of attitude medium ($f^2 = 0.296$) whilst perceived usefulness ($f^2 = 0.020$), ease of use ($f^2 = 0.080$) and subjective norm ($f^2 = 0.050$) were small respectively.

Also, the determinants of attitude towards use, i.e. perceived usefulness and ease of use accounted for 44.0% explanation of the attitude of the farmers towards the use of the technology. The four independent variables of PU: 'PEOU', 'IMG', 'SN' and 'RES' also predicted 57.0% of the variations in perceived usefulness. Finally, ANX, PLAY, PEC and ENJ predicted 49.0% of variance in perceived ease of use. The goodness of fit index of 0.545 was large enough to support the global model validity.



CHAPTER NINE

BEST PREDICTOR OF INTENTION TO ACCEPT DRONE SERVICES FROM FARMER AND FARM RELATED CHARACTERISTICS

Introduction

Chapter Nine presents the results and discusses objective five of the study which sought to examine the determinant of farmers' intention to accept drone spraying services for Fall Armyworm control in the study area from the farmers and farm related characteristics.

Best Predictor of Farmers' Intention to Accept Drone Technology Services for control of FAW from the Farmer and Farm Related Characteristics

Farmers' intentions to accept drone technology services for control of FAW was used as the dependent variable whilst farmer and farm related characteristics as the independent variables were analyzed using Ordinary Least Squares (OLS) multiple linear regression to determine the best predictors of farmers' intention to accept drone spraying services for Fall Armyworm control. The independent variables used in the regression model are; sex of farmers (X_1), age (X_2), years of farming experience (X_3), type of education (X_4), level of education (X_5) and household status (X_6). The rest are marital status (X_7), contact with extension (X_8), farm size (X_9), maize yield (X_{10}), income from sale of maize (X_{11}) and primary occupation (X_{12})

Table 39 shows that farm size was the single significant best determining factor of farmers' intention to accept drone spraying services from farmer and farm related characteristics ($F(134) = 22.61, p < 0.03$ with $R^2 = 0.13$). The adjusted R^2 value of 0.11 indicates that more than one tenth of the

variations in the farmers' intention to accept drone technology services for control of FAW is predicted by farm size cultivated to maize by the farmers ($R^2 = 0.13$). The confidence limits of the two regression coefficients of the independent variable that differed significantly from zero were lower bound = 0.06 and upper bound = 0.96.

In all farm size accounted for approximately 13 percent of the variance in the farmers' intention to accept drone spraying services for Fall Armyworm control. The mean farm size was 1.60ha hence, the size and direction (standardized beta) of the relationships between intention and the farm size indicate that, with all other variables held constant, a unit increase in farm size to 2.60ha would result in a 36 percent increase in the propensity or desire of the farmers to accept the drone spraying services for Fall Armyworm control. In other words the larger the farm size cultivated to maize by the farmers the stronger their propensity to adopt the innovation to control the invasive pest.

Table 39: Best Predictors of Farmers' Intention to Accept Drone Technology Services for control of FAW

Step of Entry	R	R^2	Adj. R^2	S.E.E	Stand. Beta	F Ratio	df	df	*P value	LB	UB
X_9	0.36	0.13	0.11	1.57	0.36	5.21	1	34	0.03	0.06	0.96

Source: Field data, Asante (2020). * $p < 0.05$, Intercept = 6.60. LB = Lower Bound, UP = Upper Bound

The results mirrored the findings of Issa et al. (2016) that analyzed the socio-economic factors that influenced farmers' adoption of improved maize production practices in Ikara Local Government Area of Kaduna State, Nigeria and concluded that the adoption of improved maize production and practices

were strongly linked to the size of the farm cultivated to maize by the farmers. Bilalib Udimal et al. (2017) also concluded that farm size had a positive and statistically meaningful impact on (Nerica) rice technology in Northern Ghana. Similarly, Donkoh et al. (2019) established that farm size is one of the important socio-economic variables influencing the adoption of improved agricultural technologies among rice farmers in Ghana. Farm size has a major positive and negative impact on adoption chances and represents a proxy for financial capability, because farmers with larger farms may be endowed with more resources to invest in environmentally friendly technologies such the drone (Serebrennikov et al., 2020).

The results, however, contradicted the findings of Nmadu et al. (2015) that studied the socio-economic factors which affected adoption of innovations by farmers in the Ondo State in Nigeria and concluded that the adoption technologies was positively influenced by sex and level of education of the farmers. Esabu and Ngwenya (2019) studied the socio-economic factors influencing adoption of conservation agriculture in the Moroto District in Uganda and established that farmers' adoption decision was influenced by access to extension services and credit, as well as sex. The findings of Sinyolo (2020) that female farmers were more likely to adopt improved maize varieties than their male counterparts and benefit more from adoption in a study of technology adoption and household food security among rural households in South Africa was not confirmed by this study.

Chapter Summary

This chapter covered the objective five which determined the main predictors of farmers' intention to accept drone technology services cor control

of FAW from the background and farm related characteristics. OLS regression was utilized to determine the best predictors from eleven independent variables. The results showed that farm size was the best predictor from the independent variables accounting for 13 percent of the variation in the propensity, tendency or desire of the farmers to accept the drone spraying services for Fall Armyworm control.



CHAPTER TEN

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

Introduction

Chapter ten presents the summary of the study, key findings as they contribute to knowledge, conclusions and recommendations of the study. The chapter also suggests the areas for further research.

Summary

The incidence and spread of Fall Army Worms (*Spodoptera frugiperda*) has hit Ghana, and some countries on the African continent since 2016. The pest is threatening food systems and food security of farm households in Africa, including Ghana. It is estimated that the FAW destroyed 45 percent of cultivated maize in 2017, translating into about 1.4 million hectares of maize fields in Ghana. The FAW which is a native pest to the tropical and sub-tropical America regions has become an important pest of maize in tropical Africa spreading, to almost all regions on the continent. The rapid spread of the pest, and anxieties over possible yield losses of an important staple crop like maize have led to the search for sustainable ways of managing and controlling the FAW. Debate on the adoption of Information Communication Technologies for Agriculture (ICTs4Ag) such as Unmanned Aerial Systems (UASs) has emerged strongly among industry players after the use of manned helicopters in Zambia by the Ministry of Agriculture during the 2016/2017 growing season.

To this end, the Technical Centre for Agriculture the Technical Centre for Agricultural and Rural Co-operation ACP-EU (CTA), funded a collaborative research project in 2019 involving the Department of Agricultural Economics and Extension of University of Cape Coast, the CSIR-

Savannah Agricultural Research Institute (CSIR-SARI), Bayer CropScience of Paris and AcquahMeyer Drone Tech Ltd., on drone technology for the application of pesticides to control Fall Armyworm (FAW) in selected districts in Northern Ghana. The goal of the research was to examine the efficacy of pesticides application for controlling FAW using drone technology. However, after the implementation of the project, little is known about the behaviour intention to accept drone spraying services for Fall Armycontrol, initiating the following questions: Are the farmers aware of the use of drone technology for agriculture? Do farmers perceive the drone technology services to be beneficial to them to control FAW in the study area? Do the costs and benefits of using drone technology services outweigh the use of the knapsack sprayer for the control of FAW in the study area from the perspective of farmers? Would the farmers accept drone technology services for Fall Armyworm control? What is the intention to accept drone spraying services for Fall Army control in the area? This study, among others, sought to find answers to these questions and determine the intention to accept drone spraying services for Fall Armyworm control.

The study adopted the mixed methods approach where both quantitative and qualitative data were collected using the descriptive cross sectional and participatory action research designs to collect data, and to answer the research questions through structured interview schedule and focus group discussion guide. Purposive and Multi-phase sampling techniques were used to select the 150 maize farmers as beneficiaries of the project jointly organized by the Department of Agricultural Economics and Extension, CSIR-SARI, Bayer CropScience and AcquahMeyer Drone Tech Ltd. Frequencies, percentages,

measures of central tendency and dispersion (means and standard deviations), chi-square, paired sample t-test, OLS regression and PLS-SEM were utilized to analyze the quantitative data whilst thematic analysis was used to analyze the qualitative data. The results were presented in line with the specific objectives of the study. Summary of key findings was presented in the proceeding paragraphs.

Key Findings of the Study

The results showed that there were more males (56.7%) than female farmers, with an average age of 41 years and a lot of years of farming experience (Mean experience =18.70 years) in maize production. Also, an overwhelming majority (93.30%) of the male farmers were married. More than two thirds (76%) of them had no formal education whilst most of the educated ones (78.60%) had pre-tertiary education from Primary to Senior High School. Furthermore, nine out of every ten (90%) farmers harvested less than 1.0Mt of maize on an average farm size of 1.60ha, and received an average income of GH¢ 1,418.33 from the sale of the maize. Because farming was their primary activity and leading source of income for most (73.30%) of them operating on family lands, they got an average of seven extension visits throughout the planting season.

Only one-fifth (19.93%) of the farmers were aware of drone technology with majority (73.08) gaining their awareness from watching television, attending church services, marriage ceremonies and funerals. The level of awareness of the maize farmers on the use of drone technology was the same in all the three study districts. Majority (57.69%) of the farmers were also aware

that the drone was used for spraying pesticides. Notwithstanding, only five farmers had participated in agricultural activities where drones were utilized.

The farmers perceived that using the drone for control of FAW was beneficial for the following reasons: ease of pesticides application, reduced negative effect on health of the sprayer, less labour required during pesticides application, saves time, and the fact that the technology enhanced the application of pesticides. Other benefits were that the drone spraying services would not necessitate a change in farmers' attitude, and beliefs because it saves money and fits well with pesticides application among the farmers. The farmers did not differ in their perceptions after both video and live drone application of pesticides. Three key factors informed farmers' perception which were technical, economic and social benefits. While the perception of the farmers on the economic and social benefits of drone technology was the same across the three districts, the perception of the farmers in the Tolon District on the technical benefits was statistically different from that of the farmers in the Mion District and West Mamprusi Municipality.

Generally, the farmers observed the costs and benefits of utilizing the drone spraying services to control Fall Armyworm to be significantly higher than the use of the knapsack during both video ($t = 3.91, p = 0.00$) and live ($t = 9.07, p = 0.00$) application of pesticides. They perceived the costs and benefits of using the drone to be significantly different from the knapsack in terms of its efficiency, performance, ease of use, and consistency with the control of FAW in the study area.

The results showed that 67.4 percent of the variation in the propensity or intention to accept drone spraying services for Fall Armyworm control was

predicted by attitude towards use, perceived usefulness, ease of use and subjective norm, with attitude having the strongest effect on behavioural intention. Perceived usefulness and ease of use accounted for 44.0% explanation of the attitude of the farmers towards the acceptance of drone spraying services for Fall Armyworm control. The four independent variables of PU (perceived ease of use, image, result demonstrability, and subjective norm) also predicted 57.0% of the variance in perceived usefulness. Finally, anxiety, playfulness, perception of external control, and perceived enjoyment predicted 49.0% of variance in PEOU. Farm size cultivated with maize by the farmers was the best predictor from the background, and farm-related characteristics variables accounting for 13% of the variation in the propensity or intention or tendency to accept drone spraying services for Fall Armyworm control. The study revealed a significant moderating effect of years of farming experience on the relationship between PEOU and PU.

Conclusions

The following conclusions were drawn in line with the key findings of the study:

1. Majority of the respondents were not aware of drone technology, however, those who were aware got to know of the digital technology by watching television; attending church services, marriage ceremonies and funerals. Almost all the farmers were participating in drone-deployed agricultural activity for the first time, even though most of them were aware of the use of the drone for applying pesticides.
2. Farmers perceived the drone was beneficial for control of FAW based on its: ease of pesticides application, reduced negative effect on health

of the sprayer, less labour required during pesticides application, time saving nature, and the technology enhances application of pesticides

3. Farmers perceived the drone to have technical, economic and social benefits. The technical benefits which is the ability of the drone to perform the task of FAW control was perceived to be more important than the economic and social benefit they would derive from the technology. Farmers in the Tolon district, however, have lower perception of the technical benefits compared with farmers in the Mion and West Mamprusi districts.
4. The use of video recording of the drone application as an extension training material provided the same impact as the live application of the drone in the field.
5. Farmers would choose the drone over the knapsack sprayer for control of FAW if they perceived drone to have high efficiency, good performance, ease of use, and consistent with the control of FAW in the study area.
6. When farmers observe the use of drone spraying services for Fall Armyworm to be useful and easy to use, they develop positive attitudes towards its use, which account for their behavioural intention to adopt the technology.
7. Farmers who cultivated farm sizes of 1.6ha or more had higher intention of adopting drone spraying services for Fall Armyworm control. Also, increasing years of farming experience resulted in improved relationship between PEOU and PU.

Recommendations

Based on the conclusions of the study, the following recommendations and policy implications were made:

1. The Ministry of Food and Agriculture through the Departments of Agriculture in the districts should use television programmes and media platforms to create awareness about the use of drone spraying services for agriculture, especially for Fall Army control in the study area. The awareness campaign should focus on the technical, economic and social benefits of drone technology.
2. The Ministry of Food and Agriculture and Drone Technology Services Providers should explore policies for rolling-out FAW control using drone technology because it is easy to use, requires less labour, saves time, and enhances better application of pesticides which reduces the negative effective of the pesticides on the environment and the sprayer.
3. MoFA and Drone Technology Services Providers looking to promote the use of drones should concentrate on the technical benefits of the technology such as limited wastage of chemicals, ease of application, precisely killing the FAW and less amount of pesticides needed during spraying.
4. Drone Technology Services Providers seeking to advertise the use of drones for FAW control can use video recordings of the field application. This would generate the same impact as the live field application of the technology on demonstration plots. This would also help reduce the cost of establishing multiple demonstration plots and the transport the equipment from one location to another.

5. When promoting the use of drone for control of FAW, Drone Technology Services Providers should focus on the efficiency, performance, ease of use, and consistency with the control of FAW which would enable farmers choose the drone as compared to the knapsack sprayer for control of FAW.
6. Maize farmers should adopt drone technology for control of FAW because the technology is efficient, performs better, it is easy to use and is consistent with the control of FAW among farmers in the study area.
7. The Ministry of Food and Agriculture through the Departments of Agriculture and Drone Technology Services Providers should work on improving the attitude of farmers towards the use of drone technology for control of FAW through field demonstrations where the usefulness and ease of use of the technology can be observed by the farmers. Additionally, significant associates who watched the demonstrations can influence the intention of the farmers to adopt the technology.
8. Drone Technology Services Providers should target farmers with farm size of 1.6ha or more since they have a higher intention to adopt the drone to control FAW compared to their counterparts operating on smaller farm sizes.
9. Farmers cultivating smaller farm sizes should collaborate with their neighbouring peers to increase their farm areas in order to access the opportunity to utilize drone spraying services for Fall Armyworm control in their fields.

10. The Ministry of Food and Agriculture should initiate policies that make agriculture with modern technologies like drones attractive to young Ghanaians, especially females to venture into agriculture.
11. The Departments of Agriculture and the Drone Technology Service Providers in a bid to improve the farmers' perceptions on ease of use, and usefulness of the innovation should focus more on farmers with more years of farming experience since they have a higher probability of improving the relationship between perceived ease of use and usefulness.

Contributions of the Study to Knowledge

The study sought to determine the acceptance of drone technology services for control of FAW in selected districts in Northern Ghana. The results show that the maize farmers have 67 percent probability of accepting drone technology services for control of FAW. The findings concerning the moderately significant relationship between attitude towards use of drone technology and behavioural intention complement and extend the previous work by Venkatesh and Bala (2008) on the extended Technology Acceptance Model (TAM 3). The authors eliminated the relationship between attitude and intention from the original Technology Acceptance Model (TAM) by Davis (1989) with the assertion that the two variables are similar constructs. This study has, however, empirically demonstrated that the variables are statistically different using the HTMT discriminant validity function in PLS-SEM. The fact that this study found the relationship between attitude and behavioural intention to be moderately significant suggests that attitude towards the use of drone

technology services is important for predicting the behavioural intention of the maize farmers to accept the technology.

The results on the significant indirect relationship between perceived external control as an anchor variable of perceived ease of use and perceived usefulness provide an opportunity for further learning. This study empirically showed that perceived ease of use mediated the indirect relationship between perceived external control and perceived usefulness which contradicts the assertion of Venkatesh and Bala (2008) that the anchor variables of perceived ease of use should not have a mediate effect over and above the determinants of perceived usefulness. The results also demonstrated the significant moderating effect of years of farming experience on the relationship between perceived ease of use and perceived usefulness.

The three factors explaining farmers' perceived benefits of drone technology for control of FAW (Technical, Economic and Social benefits) are new factors that can be used to empirically measure farmers' perceived benefits of digital technologies. From the methodological point of view, this study has empirically shown that the use of video as extension training material of pre-recorded training or demonstration can have the same effect as the live observation of the technology in the field. Figure 14 is the conceptual framework showing the contributions of this study to knowledge.

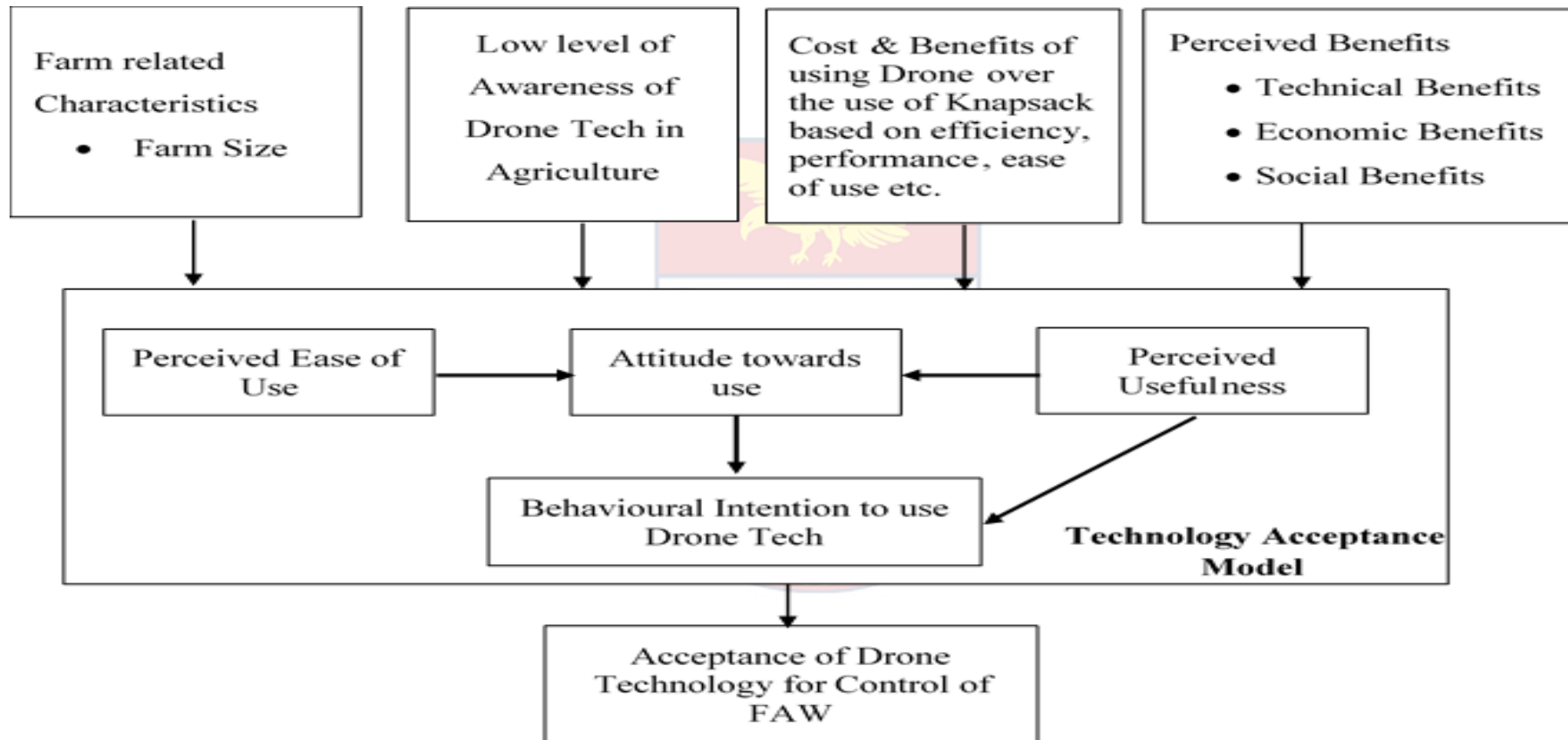


Figure 14: Conceptual framework of the study showing the contributions to knowledge

Source: Author's construct, Asante (2020).

Areas for Further Research

The following areas are recommended for future research:

1. This study focused on the Tolon and Mion Districts of the Northern Region and West Mamprusi Municipality of the North East Region of Ghana. This study should be repeated in other FAW hot spots in the country in order to validate the findings of the study.
2. Future research should be conducted on the application of drone technology for control of other invasive pests of economic importance like locust in Ghana.
3. This study found that perceived external control had a significant mediating effect on the relationship between perceived ease of use and perceived usefulness which contradict the assertion of Venkatesh and Bala (2008) that none of the anchor variables of perceived ease of use (PEOU) should not have mediating effect over and above the determinants of perceived usefulness (PU) in TAM 3. Further research should be conducted to examine the reasons for the mediating effect of perceived external control on perceived usefulness.

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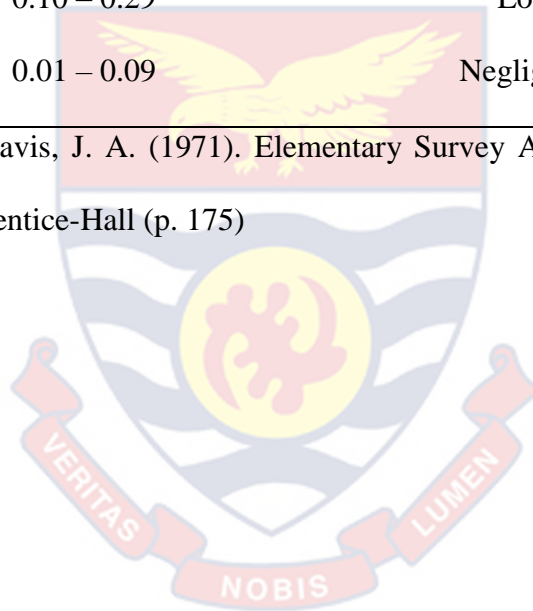
APPENDICES

APPENDIX A

Davis Convention for Describing Magnitude of Correlation Coefficient

	(r)	Magnitude of Correlation Coefficient Description
1	1.00	Perfect
2	0.70 – 0.99	Very High
3	0.50 – 0.69	Substantial
4	0.30 – 0.49	Moderate
5	0.10 – 0.29	Low
6	0.01 – 0.09	Negligible

Source: Davis, J. A. (1971). Elementary Survey Analysis. Englewood, New Jersey: Prentice-Hall (p. 175)



APPENDIX B

Ethical Clearance Letter from the Institutional Review Board, UCC

UNIVERSITY OF CAPE COAST

INSTITUTIONAL REVIEW BOARD SECRETARIAT

TEL: 0558093143 / 0508878309
E-MAIL: irb@ucc.edu.gh
OUR REF: UCC/IRB/A/2016/830
YOUR REF:
OMB NO: 0990-0279
IORG #: IORG0009096

5TH NOVEMBER, 2020

Mr. Isaac Kwasi Asante
Department of Agricultural Economics and Extension
University of Cape Coast

Dear Mr. Asante,

ETHICAL CLEARANCE – ID (UCCIRB/CANS/2020/03)

The University of Cape Coast Institutional Review Board (UCCIRB) has granted **Provisional Approval** for the implementation of your research titled **Maize Farmers' Acceptance of Drone Technology for Spraying Pesticides for the Control of Fall Army Worm in Northern Ghana**. This approval is valid from 5TH November, 2020 to 4th November, 2021. You may apply for a renewal subject to submission of all the required documents that will be prescribed by the UCCIRB.

Please note that any modification to the project must be submitted to the UCCIRB for review and approval before its implementation. You are required to submit periodic review of the protocol to the Board and a final full review to the UCCIRB on completion of the research. The UCCIRB may observe or cause to be observed procedures and records of the research during and after implementation.

You are also required to report all serious adverse events related to this study to the UCCIRB within seven days verbally and fourteen days in writing.

Always quote the protocol identification number in all future correspondence with us in relation to this protocol.

Yours faithfully,

A handwritten signature in blue ink, appearing to read 'S. Asiedu Owusu'.

Samuel Asiedu Owusu, PhD
UCCIRB Administrator

ADMINISTRATOR
INSTITUTIONAL REVIEW BOARD
UNIVERSITY OF CAPE COAST

APPENDIX C**Structured Interview Schedule for Evaluation Maize Farmers' Acceptance
of Drone Technology for Control of FAW in Northern Ghana****UNIVERSITY OF CAPE COAST****DEPARTMENT OF AGRICULTURAL ECONOMICS AND****EXTENSION****ACCEPTANCE OF DRONE-APPLIED PESTICIDE FOR THE
CONTROL OF FAW IN SELECTED DISTRICTS IN NORTHERN
GHANA**

This study is designed to assess maize farmers' acceptance of Drone applied pesticides for the control Fall Army Worm (FAW) in selected districts in northern Ghana. You have been identified as individual to provide information to achieve the objectives of the study. The interaction session is expected to last for about 45 minutes. Please respond frankly to the questions on this structured interview schedule. Be assured that all the information that will be provided will be used for the intended objectives and will be kept confidential. Your practical recommendations will be used to improve the control of FAW. Your name and phone number have been requested to assist us reach you again for follow up questions or field trip to observe fields where drones had been used to apply pesticide.

Thank You.

PART ONE: Farmer and Farm Related Characteristics

1. Name: _____
2. Phone: _____
3. Location of Farmer: _____
4. Primary occupation of respondent _____
5. Age at last birthday: _____ years
6. Sex of farmer: Male Female
7. Years of farming experience: _____ years
- 8a. Type and Level of education of farmer:

Non Formal Education if Non formal, describe _____

Formal Education No formal education
- 8b. If formal indicate the highest level:

Primary MSLC/JSS/JHS SSS/SHS Tertiary
9. Marital Status of farmers:

Married Cohabitation Single

Divorced Widowed
10. Which farmer group/organization/association do you belong? _____
11. How often do you have contact with extension agents?

Weekly Once every two weeks Once every Month

Once every Two Months Others (specify) _____
12. How many times do you contact extension agents during a planting season?

13. What is your current land holding status?

Own land Family land Leasing Renting Others, specify _____

PART TWO: Perception of Farmers on Knapsack and Drone Technology

14. Are you aware (heard/seen) the drone being used before?

Yes [] No []

15. If yes, which of the following applies to you?

Awareness of the use of drone technology	Yes	No
Used for taking videos during oil and gas exploration		
Being used for mineral exploration		
Heard about the use of drones for medical supplies		
Being used for spraying agrochemicals on farmers' fields		
Used for making films		
Used for taking pictures at ceremonies (wedding, funerals, sports, etc)		
Used by the security agencies to monitor security in the community		
Used for land surveying and plot measuring		
Others (specify):		

16. Have you participated in any programme in agriculture where drones were used?

Yes [] No []

17. If yes, which of the following applies?

MoFA [] NGOs [] FBO Members []

Research Institutions []

Others, specify:

Farmers' perception of the use of drone in the application of agrochemicals

18. You have watched the video and seen pictures of the drone being used in applying pesticide to control fall army worm in your community. Which of the following describes your observation about the drone?

- a. The drone has propellers/wings used to fly over the field []
- b. It has tank/container to store pesticides []
- c. It has nozzles for discharging the pesticides on the field []
- d. It has stands/legs to land safely []
- e. It is remotely controlled []
- f. Others

19. In your opinion to what extent, do you agree with the following statements on the use of drone to apply pesticides to control the Fall Army Worm? Rate your agreement on a 10-point scale of 1 (very low agreement) to 10 (very high agreement). 0 = cannot tell

Benefits of drone technology	0	1	2	3	4	5	6	7	8	9	10
The use of drone technology apply the exact quantity of pesticides											
Pesticides are applied to the caterpillar stage of the FAW using drone technology											
There is less wastage of chemicals in the use drones to spray pesticides											
The use of drone technology makes pesticides application easier											
The use of drone technology enhances effectiveness of pesticide application											
Less amount of pesticides are used in drone applications											

The drone technology is very beneficial																				
Drone technology is a good fit for how pesticides are applied in my community																				
Drone technology is better to other pesticide spraying methods in my community																				
Drone technology will not necessitate a change in farmers' behaviour when it comes to pesticide application for control of FAW																				
Drone technology will not necessitate a change in farmers' beliefs on the use of pesticides in the control of FAW																				
Drone technology will not necessitate a change in farmers' attitudes on the use of pesticides in the control of FAW																				
The use of drone technology saves money																				
The use of drone technology saves time																				
The use of drone technology requires less labour																				
Pesticides' detrimental environmental impact is reduced																				

20. Compare your perceive benefits of the drone to knapsack sprayers in the application of pesticides to control Fall Army Worm by indicating a number (1 – 10) for the following indicators.

1

10

(Very low)

(Very high)

Indicate Zero (0) if you cannot tell.

Knapsack	Indicators	Drone technology
	Cost of service in pesticides application	
	Duration of time in pesticides application per plot	
	In the process of application, energy is exerted	
	Spillage of pesticides during spraying	
	Drift (missing of targeted plants) during application	
	Quantity of pesticides used	
	Cost of maintenance	
	Bulkiness of the equipment	
	The impact of equipment weight in the sprayer	
	Flexibility in the manipulation of the equipment	
	The equipment's ease of use	
	Availability of the equipment	
	Reliability of the equipment	
	Skills needed to use	
	Knowledge operating the equipment	
	Affordability of the technology	
	Performance of the equipment	
	Efficiency of the equipment	
	Consistency with practice of control of FAW	
	Farmers' needs for FAW control are met consistently	
	The sprayer's health is at risk (safety)	
	Weather has an impact on how the equipment is used (wind and rain)	
	Amount of capital for acquisition of equipment	
	Support mechanisms for using the technology is available	
	Landscape/terrain of the fields	
	Availability of labour to use the technology	

PART THREE: Acceptance of Drone Technology for the control of FAW in Northern Ghana

10. What is your yield of maize in 2020? bags

1. Please indicate the extent to which you are likely to accept drone technology for the control of FAW in your farm using the 10-point scale of 1 (very lowly) to 10 (very highly). 0 = not applicable/ Can't tell

	Extent										
Perceived ease of use	0	1	2	3	4	5	6	7	8	9	10
I understand the drone is used for spraying pesticides is clear to me											
The drone to be easy to use for Fall Armyworm control											
The usage of a drone to control Fall Armyworm is straightforward											
Using drone technology will make control of FAW easier											
Using drone improves effectiveness of FAW control											
Perceived Usefulness	0	1	2	3	4	5	6	7	8	9	10
Using drone technology to control FAW improves my performance in pest control											
Using drone technology to control FAW will increase my yield											
Using drone technology to control increases income											
Using drone technology is useful in the control of FAW											
Using drone technology saves time in the control of FAW											
Drone Self-Efficacy	0	1	2	3	4	5	6	7	8	9	10

The use of drone for the control of FAW does not scare me at all.														
The use of drone for the control of FAW makes me nervous.														
The use of drone for the control of FAW make me feel uncomfortable.														
The use of drone for the control of FAW make me feel uneasy.														
Perceived Enjoyment (ENJ)	0	1	2	3	4	5	6	7	8	9	10			
I find the use of the drone for the control of FAW is enjoyable.														
Drone for the control of FAW is pleasant.														
It is fun watching the drone being used for the control of FAW														
Subjective norm (SN)	0	1	2	3	4	5	6	7	8	9	10			
People who have sway over my decisions believe I should utilize a drone to control the FAW on my farm														
People close to me believe that I should utilize the drone to control the FAW on my farm														
The AEAs will help me to access the drone for FAW control														
The AEAs will help me to access the drone for FAW control														
Voluntariness (VOL)	0	1	2	3	4	5	6	7	8	9	10			
My use of the drone for the control of FAW will be voluntary														
My AEAs will not force me to use the drone for FAW control														
Using the drone is not compulsory for the control of FAW														

Image (IMG)	0	1	2	3	4	5	6	7	8	9	10
Farmers in my community who will use the drone for control of FAW will have more prestige than those who will not											
Farmers in my community who want to utilize the drone to control FAW will be well-known											
Using the drone for the control of FAW will be a prominence emblem in my community											
Job Relevance (REL)	0	1	2	3	4	5	6	7	8	9	10
In my job as a farmer, usage of the drone for the control of FAW will be essential											
The use of a drone for FAW control will be relevant in my job as a farmer											
The use of the drone for the control of FAW is related to pesticides application on my farm											
Output Quality (OUT)	0	1	2	3	4	5	6	7	8	9	10
The quality of the output I get from the use of the drone for the control of FAW is high.											
I have no problem with the quality of the drone's output on the field											
I rate the results from the drone for the control of FAW to be excellent.											
Result Demonstrability (RES)	0	1	2	3	4	5	6	7	8	9	10
I have no difficulty telling others about the results of using the drone for the control of FAW											
I feel I could explain the risks of utilizing a drone to control FAW to other											

To me, the benefits of utilizing a drone to control FAW are evident												
I would have a hard time articulating why employing drone to operate FAW may be advantageous or not												
Behavioural intention (BI)	0	1	2	3	4	5	6	7	8	9	10	
Assuming I have access to the drone, I intend to use it for the control of FAW.												
Given that I have access to the drone, I predict that I would use it for the control of FAW												
In the upcoming planting season, I intend to employ the drone for FAW control												
Attitude (ATT)	0	1	2	3	4	5	6	7	8	9	10	
It is a good idea to use drone technology to control FAW												
The use of drone technology to control Fall Armyworm is advantageous												
It is a positive influence for me to use drone technology for the control of FAW.												
The use of drone technology to control Fall Armyworm is valuable												
The use of drone technology to manage Fall Armyworm will increase productivity												

APPENDIX D

Focus Group Discussions Guide for Maize Farmers in Northern Ghana

Section A: First Field Day

1. Can you identify the presence of Fall Army in the field?
2. What are the signs of the presence of the FAW in the maize field?
3. Can you explain the extent of damage the FAW can cause in the maize field?
4. What control methods did you adopt last year for controlling the pest?
5. What is the effectiveness of the methods you adopted last year?
6. Have you seen or heard of drone technology before?
7. Where did you see or heard of drone technology?
8. Are you aware drone technology is used in different fields?
9. Are you aware drone technology can be used in agriculture production?
10. Have you participated in an agricultural programme where drones were used?

Section B: Second Field Day

11. What is your opinion on the use drone for spraying insecticides for controlling Fall Armyworm in maize fields?
12. Do you think it will be effective for controlling the pest in the maize field?
13. In your opinion what will be the benefits of using the technology for controlling the FAW?
14. What do you think will be the benefits of using the drone as compared to the use of the Knapsack sprayer?
15. What do you think will be the cost of using the drone as compared to the use of the Knapsack sprayer?

Section C: Third Field Day

16. What is your opinion on the different fields during harvesting of the crops?
17. What is your assessment of the yield of maize from the different experimental plots?
18. What is your general assessment of the drone plot, knapsack plot and the control plots?
19. Do you think the drone will be effective for the control of FAW based on the yields harvested?



APPENDIX E

Scree Plot of Principal Component Analysis of Underlying Farmers' Benefits of Drone Technology for Control of FAW

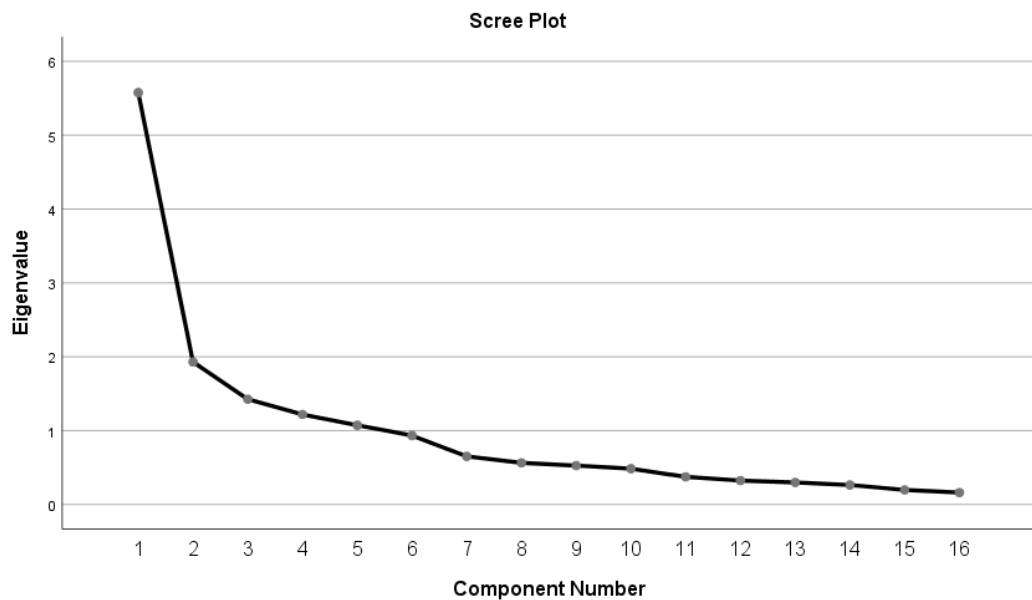


Figure 15: Scree Plot of PCA of benefits of drone technology for the control of FAW

Source: Field data, Asante (2020)

APPENDIX F

Output of Monte Carlo PCA Parallel Analysis

Table 40: Output of Monte Carlo PCA Parallel Analysis

Component Number	Actual eigenvalues from PCA	Criterion value from parallel analysis	Decision
1	5.577	1.622	accepted
2	1.930	1.497	accepted
3	1.425	1.375	accepted
4	1.219	1.285	rejected
5	1.073	1.201	rejected

Source: Field data, Asante (2020)

APPENDIX G

Summary Data View of Indicators in SmartPLS Analysis

Table 41: Summary Data View of indicators in SmartPLS

Indicators	No	MIV	ME	MED	MI	MX	SD	EK	SK
Respondents	1	0	75.5	76	1	150	43.3	-1.2	0
Sex1	2	0	0.567	1	0	1	0.496	-1.952	-0.272
Age1	3	0	41.4	40	17	79	13.555	0.075	0.628
EXP	4	0	18.7	16	1	55	11.872	1.153	1.095
PEOU1	5	0	7.767	8	5	10	1.631	-0.995	-0.149
PEOU2	6	0	8.12	8	5	10	1.446	-0.862	-0.239
PEOU3	7	0	8.033	8	5	10	1.397	-0.732	-0.238
PEOU4	8	0	7.933	8	5	10	1.459	-0.688	-0.286
PEOU5	9	0	7.993	8	5	10	1.490	-0.804	-0.269
PU1	10	0	7.567	8	4	10	1.699	-0.553	-0.379
PU2	11	0	7.58	8	4	10	1.666	-0.401	-0.403
PU3	12	0	7.473	8	4	10	1.692	-0.400	-0.421
PU4	13	0	7.607	8	4	10	1.637	-0.384	-0.408
PU5	14	0	7.7	8	4	10	1.765	-0.556	-0.549
DSE1	15	0	7.373	8	1	10	2.035	1.856	-1.189
DSE2	16	0	7.807	8	4	10	1.652	-0.385	-0.485
DSE3	17	0	7.66	8	4	10	1.661	-0.254	-0.425
PEC1	18	0	7.207	7	3	10	1.874	-0.049	-0.543
PEC2	19	0	7.133	7	3	10	1.854	0.021	-0.553
PEC3	20	0	7.513	8	6	9	1.094	-1.305	-0.050
PEC4	21	0	7.567	8	4	10	1.627	-0.192	-0.411
PEC5	22	0	7.48	8	4	10	1.595	-0.334	-0.292
PEC6	23	0	7.233	7	3	10	1.895	-0.214	-0.536
PEC7	24	0	7.02	7	3	10	1.783	-0.002	-0.579
CPLAY1	25	0	7.073	7	2	10	2.120	0.215	-0.801
CPLAY2	26	0	7.367	8	4	10	1.753	-0.458	-0.462
CPLAY3	27	0	7.473	8	4	10	1.660	-0.210	-0.536
CPLAY4	28	0	7.433	8	4	10	1.671	-0.243	-0.510
CANX1	29	0	7.22	8	2	10	2.138	0.412	-0.914
CANX2	30	0	6.967	7	3	10	2.093	-0.551	-0.432
CANX3	31	0	6.493	7	2	10	2.529	-0.692	-0.548

CANX4	32	0	6.793	7	3	10	2.044	-0.525	-0.417
ENJ1	33	0	7.64	8	4	10	1.597	-0.420	-0.287
ENJ2	34	0	7.587	8	4	10	1.650	-0.487	-0.307
ENJ3	35	0	7.78	8	4	10	1.608	-0.226	-0.453
SN1	36	0	7.447	7	4	10	1.655	-0.515	-0.248
SN2	37	0	7.613	8	4	10	1.527	-0.283	-0.121
SN3	38	0	7.447	8	2	10	1.899	0.970	-0.825
SN4	39	0	7.413	7	2	10	2.021	0.925	-0.887
VOL1	40	0	7.547	8	6	9	1.081	-1.274	-0.042
VOL2	41	0	7.467	7	2	10	1.917	0.787	-0.789
VOL3	42	0	7.267	7	2	10	2.068	0.747	-0.934
IMG1	43	0	7.36	7	4	10	1.674	-0.341	-0.386
IMG2	44	0	7.58	8	4	10	1.550	-0.029	-0.314
IMG3	45	0	7.493	7	4	10	1.603	-0.244	-0.262
REL1	46	0	7.473	8	4	10	1.696	-0.358	-0.380
REL2	47	0	7.68	8	4	10	1.667	-0.151	-0.519
REL3	48	0	7.233	7	3	10	2.001	-0.200	-0.567
OUT1	49	0	7.2	7	2	10	2.046	0.598	-0.873
OUT2	50	0	7.453	7	6	9	1.093	-1.299	0.074
OUT3	51	0	7.567	8	4	10	1.581	-0.397	-0.211
RES1	52	0	7.48	7	4	10	1.578	-0.184	-0.302
RES2	53	0	7.347	8	3	10	1.740	0.237	-0.545
RES3	54	0	7.487	7	4	10	1.628	-0.409	-0.220
RES4	55	0	7.28	7	4	10	1.752	-0.591	-0.240
BI1	56	0	7.36	8	3	10	1.694	0.288	-0.579
BI2	57	0	7.407	8	2	10	1.919	0.924	-0.828
BI3	58	0	7.087	7	3	10	2.000	-0.368	-0.459
ATT1	59	0	7.333	8	2	10	2.074	0.650	-0.911
ATT2	60	0	7.207	8	2	10	2.086	0.600	-0.879
ATT3	61	0	7.267	8	3	10	1.924	0.141	-0.737
ATT4	62	0	7.3	8	2	10	1.999	0.485	-0.789
ATT5	63	0	7.46	8	4	10	1.688	-0.43	-0.380

Source: Field data (2020). Note: MIV = Missing Values, ME = Mean, MED =

Median,

MI = Minimum Value, MX = Maximum Value, SD = Standard Deviation, EK

= Excess Kurtosis, SK = Skewness

APPENDIX H

Construct Reliability and Validity Indices of the Measurement Model

Table 42: Construct Reliability and Validity Indices of the Measurement Model

Latent Constructs	Indicators	Loadings ^a	AVE ^b	CR ^c	CA	rho_A ^d
Attitude towards Use	ATT1	0.848	0.697	0.920	0.890	0.895
	ATT2	0.851				
	ATT3	0.882				
	ATT4	0.863				
	ATT5	0.720				
Behavioural Intention	BI1	0.863	0.715	0.882	0.801	0.803
	BI2	0.832				
	BI3	0.841				
Computer Anxiety	CANX1	0.780	0.678	0.894	0.842	0.845
	CANX2	0.801				
	CANX3	0.881				
	CANX4	0.829				
Computer Playfulness	CPLAY1	0.798	0.729	0.915	0.876	0.886
	CPLAY2	0.884				
	CPLAY3	0.864				
	CPLAY4	0.867				
Computer Self-Efficacy	DSE1	0.849	0.749	0.899	0.833	0.84
	DSE2	0.886				
	DSE3	0.861				
Perceived Enjoyment	ENJ1	0.913	0.813	0.929	0.885	0.888
	ENJ2	0.910				
	ENJ3	0.882				
Image	IMG1	0.878	0.769	0.909	0.849	0.851
	IMG2	0.891				
	IMG3	0.861				
Perception of External	PEC1	0.713	0.540	0.892	0.859	0.862
	PEC2	0.743				

Control	PEC3	0.752				
	PEC4	0.731				
	PEC5	0.722				
	PEC6	0.764				
	PEC7	0.718				
Perceived	PEOU1	0.734	0.658	0.905	0.869	0.869
Ease of Use	PEOU2	0.811				
	PEOU3	0.826				
	PEOU4	0.868				
	PEOU5	0.810				
	Perceived	PU1	0.756	0.677	0.913	0.88
Usefulness	PU2	0.854				
	PU3	0.841				
	PU4	0.846				
	PU5	0.812				
	Job	REL1	0.907	0.808	0.926	0.881
Relevance	REL2	0.914				
	REL3	0.874				
	RES1	0.839	0.716	0.91	0.868	0.872
Result Demonstrability	RES2	0.867				
	RES3	0.846				
	RES4	0.831				
	Subjective	SN1	0.859	0.656	0.884	0.825
Norm	SN2	0.833				
	SN3	0.779				
	SN4	0.765				

Source: Field data, Asante (2020).

- All item loadings > 0.5 indicates Indicator Reliability (Hulland, 1999)
- All Average Variance Extracted (AVE) > 0.5 indicates Convergent Validity (Bagozzi et al., 1991; Fornell & Larcker, 1981)
- All Composite Reliability (CR) > 0.7 indicates Internal Consistency (Gefen et al., 2000)
- All Cronbach's Alpha (ρ_A) > 0.7 indicates Indicator Reliability (Nunnally, 1978)

APPENDIX I

Indicator Cross Loadings for Evaluating Discriminant Validity of the Measurement Model

Table 43: Indicator Cross Loadings of Variables in the PLS-SEM

Indicators	ATT	BI	CANX	CPLAY	CSE	IMG	REL	PEOU	ENJ	PU	PEC	RES	SN
ATT1	0.848	0.638	0.449	0.448	0.560	0.535	0.428	0.457	0.579	0.522	0.419	0.359	0.387
ATT2	0.851	0.678	0.464	0.541	0.438	0.532	0.519	0.436	0.531	0.504	0.42	0.442	0.49
ATT3	0.882	0.634	0.617	0.505	0.507	0.675	0.626	0.527	0.539	0.538	0.538	0.413	0.442
ATT4	0.863	0.613	0.583	0.442	0.495	0.619	0.594	0.470	0.546	0.463	0.432	0.446	0.379
ATT5	0.720	0.518	0.499	0.418	0.442	0.502	0.549	0.475	0.519	0.384	0.452	0.441	0.504
BI1	0.567	0.863	0.501	0.454	0.518	0.581	0.458	0.490	0.505	0.54	0.48	0.612	0.531
BI2	0.619	0.832	0.464	0.397	0.575	0.410	0.481	0.522	0.499	0.585	0.346	0.494	0.460
BI3	0.683	0.841	0.703	0.618	0.425	0.581	0.529	0.490	0.513	0.567	0.557	0.605	0.627
CANX1	0.521	0.545	0.780	0.511	0.381	0.585	0.580	0.482	0.423	0.476	0.501	0.503	0.507
CANX2	0.533	0.549	0.801	0.456	0.319	0.583	0.563	0.397	0.363	0.427	0.539	0.437	0.545

CANX3	0.482	0.548	0.881	0.545	0.400	0.535	0.492	0.383	0.353	0.448	0.502	0.459	0.477
CANX4	0.511	0.540	0.829	0.581	0.427	0.571	0.500	0.389	0.439	0.495	0.596	0.375	0.451
CPLAY1	0.483	0.449	0.507	0.798	0.319	0.611	0.612	0.378	0.486	0.440	0.651	0.448	0.491
CPLAY2	0.523	0.527	0.549	0.884	0.385	0.643	0.623	0.468	0.531	0.464	0.635	0.584	0.582
CPLAY3	0.461	0.498	0.551	0.864	0.409	0.451	0.480	0.445	0.499	0.467	0.561	0.520	0.570
CPLAY4	0.471	0.520	0.564	0.867	0.413	0.492	0.441	0.511	0.505	0.418	0.585	0.587	0.558
CSE1	0.578	0.555	0.479	0.390	0.849	0.442	0.433	0.491	0.573	0.679	0.433	0.429	0.470
CSE2	0.422	0.478	0.303	0.311	0.886	0.464	0.374	0.587	0.583	0.644	0.470	0.463	0.522
CSE3	0.533	0.520	0.439	0.466	0.861	0.529	0.415	0.591	0.611	0.622	0.552	0.404	0.535
ENJ1	0.600	0.538	0.469	0.549	0.628	0.611	0.523	0.617	0.913	0.669	0.636	0.468	0.519
ENJ2	0.610	0.545	0.498	0.549	0.687	0.603	0.618	0.588	0.910	0.719	0.631	0.526	0.603
ENJ3	0.544	0.538	0.332	0.500	0.522	0.526	0.509	0.550	0.882	0.588	0.535	0.548	0.649
IMG1	0.620	0.553	0.658	0.567	0.537	0.878	0.678	0.502	0.508	0.460	0.589	0.526	0.585
IMG2	0.605	0.576	0.580	0.629	0.518	0.891	0.699	0.533	0.610	0.526	0.563	0.585	0.585
IMG3	0.583	0.505	0.591	0.476	0.400	0.861	0.762	0.516	0.576	0.511	0.581	0.413	0.52

PEC1	0.586	0.606	0.628	0.493	0.650	0.596	0.614	0.533	0.657	0.631	0.713	0.476	0.576
PEC2	0.371	0.537	0.516	0.590	0.516	0.481	0.529	0.474	0.552	0.566	0.743	0.561	0.627
PEC3	0.397	0.295	0.308	0.454	0.411	0.447	0.434	0.495	0.545	0.501	0.752	0.309	0.512
PEC4	0.388	0.344	0.389	0.428	0.392	0.486	0.499	0.490	0.472	0.461	0.731	0.300	0.426
PEC5	0.209	0.187	0.353	0.393	0.198	0.370	0.333	0.370	0.340	0.409	0.722	0.301	0.452
PEC6	0.298	0.368	0.541	0.624	0.287	0.440	0.432	0.405	0.350	0.352	0.764	0.498	0.518
PEC7	0.468	0.425	0.603	0.680	0.337	0.531	0.498	0.395	0.435	0.381	0.718	0.565	0.523
PEOU1	0.564	0.609	0.511	0.448	0.481	0.510	0.507	0.734	0.575	0.537	0.521	0.532	0.568
PEOU2	0.371	0.457	0.276	0.261	0.545	0.392	0.317	0.811	0.470	0.574	0.425	0.414	0.405
PEOU3	0.411	0.468	0.419	0.363	0.552	0.411	0.366	0.826	0.491	0.599	0.529	0.395	0.443
PEOU4	0.437	0.428	0.406	0.531	0.479	0.519	0.522	0.868	0.518	0.513	0.571	0.473	0.431
PEOU5	0.483	0.414	0.422	0.538	0.556	0.543	0.507	0.810	0.560	0.547	0.473	0.469	0.489
PU1	0.633	0.517	0.549	0.594	0.581	0.673	0.700	0.574	0.730	0.756	0.703	0.455	0.573
PU2	0.437	0.589	0.427	0.408	0.630	0.405	0.460	0.625	0.607	0.854	0.577	0.413	0.496
PU3	0.464	0.495	0.474	0.399	0.574	0.409	0.389	0.513	0.542	0.841	0.525	0.386	0.559

PU4	0.407	0.597	0.467	0.457	0.608	0.416	0.376	0.600	0.597	0.846	0.482	0.496	0.523
PU5	0.421	0.540	0.378	0.244	0.676	0.402	0.295	0.488	0.500	0.812	0.364	0.395	0.445
REL1	0.683	0.600	0.679	0.570	0.425	0.768	0.907	0.493	0.601	0.473	0.569	0.433	0.544
REL2	0.537	0.452	0.565	0.591	0.399	0.786	0.914	0.492	0.558	0.508	0.609	0.391	0.567
REL3	0.536	0.52	0.525	0.519	0.440	0.638	0.874	0.502	0.489	0.506	0.598	0.448	0.541
RES1	0.381	0.554	0.475	0.559	0.437	0.520	0.504	0.493	0.54	0.493	0.493	0.839	0.565
RES2	0.425	0.561	0.479	0.555	0.432	0.459	0.304	0.371	0.48	0.44	0.476	0.867	0.554
RES3	0.459	0.523	0.450	0.499	0.441	0.516	0.452	0.548	0.422	0.429	0.479	0.846	0.470
RES4	0.437	0.657	0.437	0.516	0.371	0.468	0.319	0.512	0.471	0.404	0.528	0.831	0.599
SN1	0.499	0.610	0.571	0.553	0.489	0.510	0.574	0.489	0.565	0.567	0.639	0.531	0.859
SN2	0.387	0.540	0.418	0.420	0.551	0.502	0.462	0.517	0.586	0.633	0.600	0.56	0.833
SN3	0.482	0.560	0.540	0.535	0.503	0.539	0.464	0.481	0.517	0.454	0.494	0.513	0.779
SN4	0.312	0.334	0.423	0.615	0.342	0.547	0.488	0.384	0.422	0.369	0.568	0.489	0.765

Source: Field data, Asante (2020). NB: Indicator Cross Loading Criteria (Chin, 1988)

APPENDIX J

Fornell-Larcker Criterion for Evaluating Discriminant Validity of the Measurement Model

Table 44: Fornell-Larcker Criterion for evaluation Discriminant Validity

Items	ATT	BI	CANX	CPLAY	CSE	IMG	REL	PEUOU	ENJ	PU	PEC	RES	SN
ATT	0.835												
BI	0.741	0.845											
CANX	0.625	0.665	0.824										
CPLAY	0.566	0.586	0.636	0.854									
CSE	0.585	0.595	0.465	0.450	0.865								
IMG	0.687	0.622	0.694	0.638	0.555	0.877							
REL	0.649	0.581	0.654	0.623	0.469	0.813	0.899						
PEOU	0.565	0.592	0.508	0.532	0.646	0.590	0.552	0.811					
ENJ	0.650	0.599	0.483	0.591	0.681	0.645	0.610	0.649	0.902				
PU	0.581	0.668	0.564	0.522	0.746	0.569	0.552	0.686	0.732	0.823			
PEC	0.541	0.550	0.650	0.707	0.564	0.659	0.660	0.625	0.668	0.655	0.735		
RES	0.501	0.676	0.545	0.631	0.499	0.582	0.472	0.568	0.568	0.525	0.583	0.846	
SN	0.525	0.642	0.605	0.646	0.59	0.643	0.613	0.582	0.651	0.635	0.710	0.647	0.810

Source: Field data, Asante (2020) NB: The diagonals are the square root of the AVE of the latent variables and indicate the highest in any row or column (Fornell & Larcker, 1981).

APPENDIX K

Heterotrait-Monotrait (HTMT) Criterion for Evaluating Discriminant Validity of the Measurement Model**Table 45: Heterotrait-Monotrait (HTMT) Criterion for Evaluating Discriminant Validity**

	ATT	BI	CANX	CPLAY	IMG	PEOU	ENJ	PU	PEC	RES	SN
ATT											
BI	0.879										
CANX	0.738	0.804									
CPLAY	0.582	0.669	0.692								
IMG	0.802	0.73	0.821	0.705							
PEOU	0.693	0.778	0.618	0.567	0.657						
ENJ	0.763	0.711	0.573	0.578	0.755	0.737					
PU	0.692	0.845	0.666	0.553	0.625	0.806	0.824				
PEC	0.624	0.647	0.781	0.805	0.777	0.702	0.677	0.681			
RES	0.565	0.815	0.598	0.69	0.661	0.643	0.591	0.573	0.611		
SN	0.629	0.758	0.717	0.723	0.745	0.651	0.778	0.729	0.809	0.727	

Source: Field data, Asante (2020). N.B: The Shaded diagonals are the inter-construct correlations of the constructs of the TAM 3 variables used

in the study (Kline, 2011).

APPENDIX L

Collinearity Diagnosis of the PLS-SEM Exogenous Constructs

Table 46: Variance Inflation Factor (VIF) values of the exogenous constructs

Constructs	ATT	BI	IMG	PEOU	PU
ATT		1.865			
BI					
CANX				1.935	
CPLAY				2.040	
IMG					1.879
PEOU	1.882	2.119			1.68
ENJ				1.700	
PU	1.882	2.455			
PEC				2.718	
RES					1.888
SN		1.821	1.000		2.008

Source: PLS-SEM Analysis, Asante (2020)

APPENDIX M

Global goodness of fit index (GOF)

GOF = Square root of $AVE \times R^2$

Table 47: Global goodness of fit index (GOF) of th PLS-SEM

Variables	AVE	R2
Attitude towards use (ATT)	0.697	0.44
Behavioural Intention (BI)	0.715	0.674
Anxiety (ANX)	0.678	
Playfulness (PLAY)	0.729	
Perceived Enjoyment (PENJ)	0.813	
Image (IMG)	0.769	0.376
Perceived External Control (PEC)	0.54	
Perceived Ease of Use (PEOU)	0.658	0.49
Perceived Usefulness (PU)	0.677	0.57
Results Demonstrability (RES)	0.716	
Subjective Norm (SN)	0.656	
Average Values	0.695	0.51
$AVE \times R^2$	0.354	
GOF = Square root of $AVE \times R^2$	0.545	

Source: PLS-SEM Analysis, Asante (2020)