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Influence of digital financial inclusion on productivity of smallholder farming households in Mwea, Kirinyaga County, Kenya.

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Influence of digital financial inclusion on productivity of smallholder farming households in Mwea, Kirinyaga County, Kenya

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Declaration

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, this thesis contains no materials previously published or written by any other person except where due reference is made in the thesis itself.

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Abstract

Economies with high levels of digital financial inclusion is reported in literature to have higher levels of productivity. However, the small-scale farmers in Mwea have been complaining of declining agricultural productivity. The farmers have been encouraged to enrol in digital inclusion platforms in the recent years. This study sought to investigate the influence of digital financial inclusion on productivity of smallholder farming households in Mwea, Kirinyaga County, Kenya. Specifically, the study sought to determine the influence of digital payments on productivity of smallholder farming households; examine the effect of digital lending on productivity of smallholder farming households and estimate the influence of digital insurance on productivity of smallholder farming households in Mwea, Kirinyaga County, Kenya. The philosophy underpinning this study was positivism and this study adopts descriptive correlational research design. This study targeted 7022 smallholder farming households in Mwea constituency of Kirinyaga County. The sample size of households in Mwea was determined using the Yamane sampling formula. Snowballing sampling technique was adopted to select 378 households. Primary data was collected using semi-structured questionnaires administered through assistance of research assistants. Review by experts determined the validity of the data collection instruments. The researcher undertook a pilot test on 38 households in Kirinyaga Central to assure on the reliability of responses through the Cronbach alpha value test. SPSS version 25 was proposed to guide data management and to facilitate synthesis of data trough descriptive and ordinal regression analysis. Correlation analysis results indicated that digital payment, digital lending and digital insurance had a significant relationship with agricultural productivity. Regression analysis results also showed that digital payment had a positive effect on agricultural productivity of the selected households. This was shown by the increasing odds for higher outcome due to increased digital payments. The findings also showed that the odds of higher agricultural productivity increased with digital lending indicating that digital lending had a positive effect on agricultural productivity. Further, there were higher odds of higher agricultural productivity when digital insurance was adopted. The study concludes that the digital financial inclusion in Mwea is low reflected in the low uptake of digital financial products. The study also concludes that digital financial inclusion has a positive effect on the productivity of smallholder farming households in Mwea, Kirinyaga County, Kenya. The study recommends that the policy makers come up with policies geared towards increased financial inclusion among the smallholder farmers. The study also recommends that households in Mwea increase the usage of digital payments, lending and insurance for increased agricultural productivity. Future research needs to be done using different measures of digital financial inclusion and productivity. Future research also needs to be done based on other constituencies, and other influencers of productivity.

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Dedication

I dedicate this proposal to my Late Mother, Naomi Wangari Kamicha who has been the pillar of my strength and who left earlier than I was prepared for, and to my Wife Peris Wambui Mukaru and children Wangari, Njeri and Ndura who have encouraged and challenged me along this arduous but fulfilling journey.

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List of Abbreviations and Acronyms

AGRA	Alliance for a Green Revolution in Africa
APIs	Application Programming Interface
CFA	Confirmatory Factor Analysis
E.G	For Example
EFA	Exploratory Factor Analysis
FinTech	Financial Technology
GDP	Gross Domestic Product
ICT	Information Communication Technology
IFC	Interantional Financing Corporation
KNBS	Kenya National Bureau of Statistics
KSh	Kenya Shilling
M-Pesa	Mobile Pesa
MSME	Micro, Small and Medium Enterprises
NACOSTI	National Commission for Science, Technology and Innovation
P2P	Person to Person
POS	Point of Sale
QR	Quick Response
SEM	Structural Equation Modelling
SME	Small and Medium Enterprise
SPSS	Statistical Package for Social Science
TAM	Technology Adoption Model
TFP	Total Factor Productivity
UK	United Kingdom

Operational Definition Of Terms

Financial inclusion	Access to useful and affordable financial services by individuals and businesses
Agricultural productivity	Quantity of agricultural output produced by a farm with a given level of inputs
Digital payment	This is a non-cash transaction processed through digital channels
Digital lending	The process of giving credit to individuals and organizations through digital channels
Digital insurance	This is the use of online platforms to sell and buy insurance policies

CHAPTER ONE

INTRODUCTION TO THE STUDY

This chapter introduces the study. It gives the background and the research problem. The study also gives the research objectives as well as the research questions. The significance and scope of the study are also given within the chapter.

1.1 Background to the Study

A vibrant, robust and well-performing agricultural sector is a key pillar to the Kenyan economy. Globally, small-holder farmers consist of approximately two billion persons, that is, almost 500 million households (World Bank, 2019). In developing countries small-scale households play a vital role in feeding the populace as well as meeting the international demand for agricultural commodities (IFC, 2020). According to AGRA (2017), small-households farming accounts for 80 percent of the region farmlands. Currently, the food market in Sub-Sahara Africa is valued in excess of United States $ 300 billion and it is projected to be worth over more than $ 1 trillion by the year 2030. In Kenya, agriculture contributes more than 50 percent of the country's Gross Domestic Product (GDP) while accounting for 60 percent of employment (Birch, 2018). Small-holder farmers dominate the agricultural sector and account for 78 percent of the overall agricultural production as well as 70 percent of agricultural commercial production (World Bank, 2019). According to World Bank (2019), Kenyan households engaged in agricultural activities contributed 31.4 percent to poverty reduction in rural areas, in addition to being the main source of income to most of the households. The contribution of agriculture to Kenya's GDP is mainly driven by horticulture and cash crops, however, the production, in particular for cereals, is low (Birch, 2018).

The World Bank (2019) recommends enhancement of financial inclusion to small scale farmers as one of the measures that would help improve productivity and performance of the agricultural sector. However, the report notes that traditional financial inclusion needed to in the sector is lacking. Furthermore, traditional finance has inherent disadvantages ranging from insufficient coverage, high cost and its inability to spread widely to the agricultural sector. The development of digital inclusive finance is believed to have the ability to compensate for the shortcomings (Janzen, Magnan, & Mullally, 2021). Buttressing the point, Janzen et. al. (2021) posits that small-holder farmers in developing countries such as Kenya on their own are not able to raise required capital to invest in more productive inputs. The study further points out, the farmers are not financially included. Globally, financial inclusion is increasing being recognized as major tool for economic development and poverty reduction, creation of job opportunities as well as aiding in improving agricultural productivity (Omeje, Mba, Ugwu, Amuka, & Agamah, 2021). The growth of digital inclusive finance seems as if it has the ability to sought out problems presented by traditional finance, that does not cover small-holder farmers and agriculture comprehensively, while providing better financial services (Liu, Liu, & Zhou, 2021). This improves farmers enthusiasm that is crucial for agricultural productivity. Digital finance inclusion, alternatively referred to as FinTech, aids in tackling the challenges faced by small holder farmers in accessing the mainstream financial services products such as payments, financing, insurance and investments (Ernst & Young, 2020).

The digitization of payments to farmers contributes in making agricultural supply chains more transparent, resilient and reduces transaction costs which aids in enhancing productivity. On the other hand, digital credit would allow farmers, who would otherwise be excluded from traditional finance, to finance higher upfront costs of more productive crops in addition to acting as a buffer in the event of unexpected shocks. According to Asia-Pacific Economic Cooperation Secretariat (2017) there are three principal barriers to improving agricultural sector efficiency and productivity and which can be addressed by digital inclusion. The first is the inefficiencies in the cash-based payments with the attendants' limitations such as high cost of distributing cash, opaque pricing and physical barriers. The other two includes insufficient access to credit and the inability to hedge against risk. The report by Asia-Pacific Economic Cooperation Secretariat, (2017) contends that digital payments will not only improve value chain transactions, but also reduce costs and improve convenience for farmers. Furthermore, this will lower the cost of providing financing to small scale farmers and also connect smallholders with digital savings and insurance products.

Globally, risk is an inherent characteristic in agricultural production. However, in most of the developing countries, small-holder farmers have limited access to risk mitigation strategies such as insurance (Skryl, Osipov, & Zhevora, 2019). Barriers limiting small-holder farmers includes lack of awareness, high costs associated with data collection and processing of claims and limited insurance products targeting the farmers.

According to Miller, (2019), digitizing agricultural insurance helps in reducing barriers to access to insurance and boosts the effectiveness of the insurance. Digital tools facilitate the uptake of insurance and reduce transaction costs while improving on efficiency of the processes of agriculture insurance. In the event of shocks hitting the households, agricultural insurance improves on their resilience while ensuring stability, productivity and sustainability of small-holder agricultural households (Miller, 2019). Despite the initiatives to support insurance products for smallholder farmers, the impact of such approaches remains unclear. Summing up, evidence suggests that productivity in the agricultural sector can benefit from better access to financial instruments tailored to the needs of small-holder farmers.

Data from the KNBS (2020) indicate that the performance of the agricultural sector in Kenya slowed down from 6 percent in 2018 to 3.6 percent in 2019 accounting for a sizeable portion of slowdown in real GDP growth 6.3 percent to 5.4 percent over the same period. Digital lenders can offer small value loans to a larger number of borrowers with limited credit checks (Carlson, 2017). This has increased the adoption of digital credit especially among small scale farmers and businesses in Africa and beyond. However, digital credit has high rates of interest which makes digital credit very expensive compared traditional loans from banks and other financial institutions (Ozili, 2018). This has made small borrowers to suffer the high costs which may outdo the benefits of digital financing.

1.1.1 Digital Financial inclusion

World Bank (2014) defined financial inclusion as access and usage of useful and affordable financial products and services (transactions, payments, savings, credit and insurance) that meet the needs of individuals and delivered in a responsible and sustainable way. In this way, financial inclusion offers the individual some benefits which include lower transaction costs for daily economic activities, the ability to plan for long-term needs, and the opportunity to create buffers for unexpected emergencies. The term “digital financial inclusion”, defined as digital access to and use of formal financial services by underserved and excluded populations (Alexander & Karametaxas, 2021).

It is important to note that access to a transaction account is the first step toward digital financial inclusion since it allows people to save money, send and receive payments using digital channels like mobile phones and internet. In the context of this study digital financial inclusion means small scale farm households that have access to and use of convenient digital financial products and services (account ownership, savings, ownership of insurance products any other financial product) including mobile money services that meet their varying needs.

Digital financial inclusion involves the deployment of the cost-saving digital means to reach currently financially excluded and underserved populations with a range of formal financial services suited to their needs that are responsibly delivered at a cost affordable to customers and sustainable for providers. Digital financial inclusion represents more than a payment instrument. Digital financial services greatly reduce transaction costs in rural areas because of their lower marginal cost (Guo, Kong & Wang, 2018). Relying on ICT, such financial services need not establish physical outlets. Although new digital technologies often face higher initial costs to establish digital system, their marginal cost then tends toward zero with the increase of business volume (Liao, Yao & Hu, 2020). Second, digital finance may overcome information asymmetry by developing ICT (Gomber, Koch & Siering, 2021). Online products and services, such as online shopping platforms and online social networks, produce a large amount of information on individuals, which will alleviate information asymmetry between individuals and financial institutions (Guo et al, 2019).

Digital financial inclusion involves digital payments through channels like mobile banking, electronic banking etc which allow the small-scale farmer to pay for inputs as well as receive funds digitally. Digital payments are non-cash transactions processed through digital channels. These include digital commerce and mobile point-of sale (POS) payments (Digital Payments Report 2019, Statista). Digital commerce refers to consumer transactions directly related to online shopping for products and services that can be made via various payment methods (e.g., credit cards, direct debit, invoice, or online payment providers, such as PayPal and AliPay). Non-bank e-money issuers such as e-commerce platforms or telecom operators with large user bases, for example, Go-Jek, Alibaba, and Safaricom, are enabling digital payments and simple savings instruments using mobile phones, QR codes, and agent networks. The ability to securely send small payments cheaply has made new products and services, such as pay-as-you-go solar, viable for customers in remote areas. Third parties, such as budgeting apps, can now initiate payments of users' bank and payment card accounts or obtain financial transaction data through open APIs to establish consumer consent and promote competition (UK, India, and Mexico). Mobile POS payments are transactions processed via "mobile wallets" (e.g., M-Pesa) where the payment is made by a contactless interaction of the mobile application with a suiTable payment terminal belonging to the merchant. Both digital commerce and mobile payments have increased in agriculture sector in the recent years.

Digital technology may improve access to credit for farmers who lack collateral through digital financing (Bruett, 2007). Based on big data analysis, cloud computing, and other technologies, digital finance, such as P2P lending, uses new credit score mechanisms to create collateral-free loan products (Liao, Yao & Hu, 2020). In Kenya, mobile money is used mainly for digital payments (Van Hove & Dubus, 2019). Several recent papers also provide some evidence on positive (Suri & Jack, 2016) or negative (Van Hove & Dubus, 2019) correlations between this payment tool and productivity.

Digital credit has already been delivered to millions of poorer households in Kenya, Tanzania, Zambia, and Ghana. Digital lending can be tailored to user needs and facilitated using machine-learning models that leverage alternative data, such as payments, e-commerce, social media, or mobile phone activity, without the need for human intervention. For example, Zenka loans require three minutes to apply, one second to approve, and zero bank staff. Platform-based models for invoice finance have created marketplaces for small scale farming businesses' receivables, and e-commerce platforms leverage data on sellers to offer working capital. Marketplace lending offers viable alternatives for the farmers that are left unserved by traditional models. Platform-based models for reverse factoring have created a market place for farmer's receivables.

Digital insurance products have come up in the recent years. Although less mature than digital payments and lending, basic digital insurance products, including vehicle, travel, and health insurance, that can be tailored to meet specific user needs and be delivered on demand through apps or marketplaces have emerged. Initial innovations were around delivering small-value policies using digital channels to match costs to revenue of such small policies. Digital insurance has growth extensively across the globe. Basic "insurtech" solutions are available in South Africa and Brazil, but also less developed countries such as Tanzania, Rwanda, and Pakistan. Similar to the case of digital credit, machine-learning models can leverage alternative data, including from telematics and wearables, to make risk classification and product pricing more accurate. Some fintech startups are using satellite data and machine learning to offer digital insurance and loans to farmers.

Since 2014, India has embarked on one of the most ambitious financial inclusion initiatives ever seen anywhere in the world, bringing over 330 million people into the formal financial sector. This report tells the story of this growth. It dissects the major trends and drivers behind them, identifies key actors and the roles that they have played, and presents a roadmap for how the next phase of digital financial inclusion in India can be made more effective and more inclusive.

Financial inclusion in Kenya has improved in the recent years. However, the financial inclusion is still low. According to Central Bank of Kenya (2023), only 42% of the Kenyan population have an account to a financial institution. Further, less than 50% of the bank accounts are linked to a mobile account. This is an indication that the digital financial inclusion in Kenya is still low. In Mwea, financial inclusion is very low with less than 23% of the small-scale farmers having digital bank accounts.

Digital financial inclusion has shown various gaps. For example, Kandpal and Mehrotra (2019) studied the role of fintech and digital financial services in India. They indicated that India has adopted innovative mobile-based banking solutions for increased financial inclusion in the rural areas. The display gaps in that they focused on mobile-based transactions with digital financial inclusion focusing on all transactions done electronically but not only through mobile phones. This study was also done in India showing contextual gaps. Ozili (2021) studied digital financial inclusion in Nigeria. The study focused on digital financial inclusion in Nigeria showing a contextual gap as the current study was based in Kenya. Khera, Ng, Ogawa, and Sahay (2022) measured digital financial inclusion in emerging market and developing economies. The authors adopted digital financial inclusion index covering 52 emerging market and developing economies. However, the current study was based on primary data from small scale farmers in Mwea analyzed through ordinal regression. This created a methodological gap.

1.1.2 Agricultural Productivity

Agricultural productivity is measured as the ratio of agricultural outputs to inputs. While individual products are usually measured by weight, which is known as crop yield, varying products make measuring overall agricultural output difficult (Gollin, 2019). Total Factor Productivity (TFP) growth – the efficiency with which producers combine inputs to make outputs – has driven most of the growth in agricultural production in the last two decades, though progress is uneven across countries and sector. Productivity gaps remain significant among farms, and improving the productivity of farms lagging behind remains a challenge for structural adjustment, even for high performing countries.

Hamory et al (2021) reevaluated agricultural productivity gaps with longitudinal microdata. This paper used long-run individual-level panel data from two low-income countries (Indonesia and Kenya) to explore these gaps. This was a comparative study which creates a methodological gap where the current study is not a comparative one. Baležentis et al (2021) did an analysis of environmental total factor productivity evolution in European agricultural sector. The study despite looking at agricultural productivity, it was based on environmental total factor productivity with the current based on general productivity. This creates a conceptual gap. Teye and Quarshie (2022) studied the impact of agricultural finance on technology adoption, agricultural productivity and rural household economic wellbeing in Ghana. The study was done in Ghana with the current done in the Kenyan county of Kirinyaga. This creates the need to investigate agricultural productivity as a variable.

As financial inclusion enhances access to financial services such as credit, savings, insurance and other on-financial products, farmers are able to meet consumption and social demands (food, health care, school fees, and funeral expenses) without having to divert funds from farming investments (Adeola and Evans, 2017). This process has the potential for investing the needed funds into farming thus increasing their output and production capacity. Since financial inclusion enhances access to financial services, many of the cash-starved farmers who dominate the rural landscape are likely to adopt the most productivity-enhancing practices and may translate into high-return, above subsistence-oriented production practices that may provide diversification and promote rural livelihood strategies (Olaniyi,2017). Additionally, in an inclusive financial system, farmers are able to borrow at low cost, make timely investment decisions, allocate productive resources efficiently and expand their productive capacities (Adeola & Evans, 2017; Evans & Lawanson, 2017; Olaniyi, 2017)

Hong, Tian and Wang (2022) studied Digital Inclusive Finance, agricultural industrial structure optimization and agricultural green total factor productivity. This study shows conceptual gaps as it includes agricultural industrial structure optimization in its analysis. The study also adopted the green total factor for productivity which is different form the measures adopted in the current research. Atakli and Agbenyo (2020) studied the nexus between financial inclusion, gender and agriculture productivity in Ghana. The study adopted financial inclusion other than digital financial inclusion while including gender in its analysis. This showed a conceptual gap. The study was done in Ghana with the current study done in Kenya showing a contextual gap. This created the need for a study on digital financial inclusion and agricultural productivity.

1.1.3 Small-scale Farming Households in Mwea Constituency

The main crops grown in Mwea include rice, chillies, onions, watermelons, cucumbers and tomatoes. Majority of the farmers are small scale farmers who have small tracts of land with majority being under the Mwea irrigation scheme among other schemes like Bura. Rice is the third most important staple food after maize and wheat. Historically, rice is a cash crop for rural producers with the Mwea Irrigation Scheme, in Kirinyaga County accounting for 75.3 per cent of total paddy rice production in Kenya. In the period 2019, rice production by the Mwea Irrigation Scheme increased by 34.5 per cent to 121.0 thousand tonnes. Gross value of rice output in the Scheme increased from KSh. 6.1 billion in 2018 to KSh. 8.7 billion in 2019, while payment to plot-holders increased from KSh 3.5 billion to KSh 5.8 billion in 2019 (KNBS, 2020). Paddy rice production increased by 42.7 percent to 160 thousand metric tons. The farmers have been expanding in various facets and even explored other value chains like maize farming in addition to Rice farming which is the main farming activity by the farmers.

1.2 Research Problem

The farmers in Mwea have experienced inadequate access to financing given the increased condition for access to funding from banks and other financial institutions. Mwea East also experiences low levels of digital financial inclusion given that it’s a rural region with low access to digital platforms where digital financing is offered. The region also has low literacy levels among the small-scale farmers with the educated migrating to the city for greener pastures. The cost of using the technology as well as poor internet connection in areas where smallholder farmers are located have also been challenges to financial inclusion in Mwea. Kirinyaga county has more than 87% of the economy derived from agriculture with more than 67% being under small scale farming (KNBS, 2021). Mwea subcounties (East and West) make the highest contribution to the agricultural productivity in Kirinyaga county. Despite this, the small-scale farmers in Mwea have experienced reduced and poor agricultural productivity in the recent years (Kirinyaga County Integrated Report, 2021). Could this be accrued to the challenges in digital financial inclusion among the farmers.

Despite consensus that small-holder farming household play a crucial role in a country's economic growth, gaps still do exist in extant literature on the role played by digital financial inclusion on productivity of small holder farming households. The existing empirical literature shows no consensus on the effect of digital financial inclusion on productivity. A growing strand of literature indicates that financial inclusion can improve productivity while a separate strand indicates that financial inclusion is unrelated to productivity. Few studies that have conceptualized digital financial inclusion and productivity of smallholder farming households are done internationally but not locally.

The review of the previous empirical studies has brought about a number of research gaps. In the first instance, most studies mobile money platforms have focused on one aspect such as transaction costs and performance. For the studies done on digital financial inclusions, the studies have focused on other sectors other than farming. Finally, the reviewed studies have not contextualized their research within Mwea, Kirinyaga County. For example, Mararo (2018) investigated the effect of mobile payments on the growth of 100 SMEs in Nakuru town. This study despite looking at digital financial inclusion elements, the study related this to the performance. The study was based in SMEs in Nakuru other than small scale farmers in Mwea. Further, Abayo and Oloko, (2019) studied the efffect of M-shwari loan on growth of SMEs in Kisumu Kenya. The study looked at Mshwari loans as one of the elements of financial inclusion and firm growth other than agricultural productivity showing conceptual gap. The study also focused on SMEs in Kisumu Kenya other than farmers in Mwea showing a contextual gap. The proposed study filled the gaps by investigating the effect of digital financial inclusion on productivity of smallholder farming households in Mwea, Kirinyaga County, Kenya.

1.3 Research Objectives

1.3.1 General Objective

The general objective of this study is to gauge the influence of digital financial inclusion on productivity of smallholder farming households in Mwea, Kirinyaga County, Kenya.

1.3.2 Specific objectives

Specifically, the proposed study sought to:

i. Determine the influence of digital payments on productivity of smallholder farming households in Mwea, Kirinyaga County, Kenya.
ii. Examine the effect of digital lending on productivity of smallholder farming households in Mwea, Kirinyaga County, Kenya.
iii. Establish the influence of digital insurance on productivity of smallholder farming households in Mwea, Kirinyaga County, Kenya.

1.4 Research Questions

The study was based on the following research questions:

i. What is the influence of digital payments on productivity of smallholder farming households in Mwea, Kirinyaga County, Kenya?
ii. What is the effect of digital lending on productivity of smallholder farming households in Mwea, Kirinyaga County, Kenya?
iii. How does digital insurance influence productivity of smallholder farming households in Mwea, Kirinyaga County, Kenya?

1.5 Significance of the Study

1.5.1 To policy makers

The findings of this study may also be valuable for policy makers like the ministry of agriculture. The policy makers, through an understanding on the influence of digital financial inclusion on productivity of smallholder farming households, would be able to formulate policies relating to small scale farming. The policies would be geared towards increased agricultural productivity among smallholder farming households through digital financial inclusions.

1.5.2 To Practitioners

This study will be significant to various stakeholders. The study findings will create an understanding on the influence of digital financial inclusion on productivity of smallholder farming households. This will make the findings valuable for small scale farm holders in Mwea. The farmers would be able to come up with strategies that would enable them to enhance their agricultural productivity through digital financial inclusion.

1.5.3 To Scholars and Researchers

The study on the influence of digital financial inclusion on productivity of smallholder farming households would contribute to the literature available in the area of study. Scholars would hence be able to access literature that would enable them to handle their assignments with ease. The researchers with interest in the area of digital financial inclusion and agricultural productivity would find this study as a base for further research. This would be based on the research gaps in the proposed study.

1.6 Scope of the Study

From the review of empirical literature, the influence of digital financial inclusion on productivity of smallholder farming household in Mwea remains unexplored. Thus, the current study strived to examine the influence of digital financial inclusion on productivity of smallholder farming households in Mwea, Kenya. This study was done for a period of 12 months from June 2022 to June 2023.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

The chapter was devoted to review of literature, both theoretical review and empirical review to bring forth an understanding on what exists. At first, the chapter provided a detailed review of theories that the study is anchored on. In the section that followed, a pairwise review of extant literature in line with the hypothesised relationship is carried out. This brought in for knowledge gaps along the methodological, contextual and conceptual realms. A conceptual model, schematized along arguments in literature was presented to demonstrate the relationship among the study variables in line with arguments in literature.

2.2 Theoretical Review

The two variables of this study, digital financial inclusion and productivity in smallholder farming households were anchored on two theories. The theories were the Innovation Diffusion Theory (Rogers, 1962) and the Technology Acceptance Model (Davis, 1989). This study links the two theories to provide an exclusive explanation of the relationship. The multi-theory approach was adopted to ensure that all the variables are theoretically explained in the proposal. This is because no single theory explained the variables adopted in this study conclusively.

2.2.1 The Innovation Diffusion Theory

The innovation diffusion theory was founded by Rogers (1962). The early scholar sought to explain the sTable factors that led to spread of innovations across firms. According to Rogers (1962) an innovation is related to a new way of doing things, novel ideas or objects within the social realms. Innovation diffusion, on the other hand, is the practice of adopting the novel object and ideas in the society over time. According to Rogers (1962), new technology adoption is a lengthy process, relatively, and undergoes a process before it is fully adopted by the society. Rogers (1962) broke down the innovation adoption into five steps; cognizance, interest, assesment, pilot and eventually adoption. However, it is imperative that the new technology inputs and output be in a form that is measurable if the novelty is to get acceptance, and fully take shape in a firm and have ability to satisy the users (Pinho, Franco & Mendes, 2021).

Rogers (2003) extended the innovation diffusion theory further by elucidating that innovations adoption had more distinct features than the five steps, and described the technology adoption process as uncertainty reduction process. The attributes that were touted as critical in reducing uncertainty included first, the relative advantage, the extent to which new technology was viewed as being better than the old one. The second characteristic was named as compatibility, that is consistent with the present need, while the third factor was complexity. However, complexity was negatively related to adoption. trialability and observability were the last two factors (Rodgers, 2003). It is however imperative, Rodgers (2003) argued that users of new technology are adviced of the advantages, consequencies and disadvantages of either adoption or non-adoption.

Amongst the critics of the innovation diffusion theory was Pinho, Franco and Mendes (2021) whose views that Rodgers (2003) theory was that it took a different outlook from other theories of change. Lundbland (2003) argues that innovation diffusion theory does not focus on changing people but views change as being progressive in a way that would fit better to individual needs. In innovation diffusion theory, the argument is that technology change in rensponse to the needs of the people. Innovation diffusion theory focusses on new item characterstics and holds that for acceptabilty of new technology to take root, trialability, complexity, comparability obsevability and relative advantage (Rodgers, 2003). Rogers (2003) further contends that how an organisation perceives these attributes determines the level on new innovation adoption.

Digital lending and insurance are new products that have been adopted with time and hence farmers need adopt the technologies in financial inclusion for increased productivity. When the accessibility of digital financing platforms increases among small-scale farmers, the farmers find themselves adopting such platforms for increased productivity. By adopting the digital lending and payment platforms, the farmers can access capital required for their farmland which in turn improves agricultural productivity. In addition, the adoption of digital insurance services offer farmers a safety net against climatic risks, mitigating financial losses and ensuring greater stability in their livelihoods.

2.2.2 Technology-Acceptance-Model

Davis (1989) postulated the Technology Adoption Model (TAM) and has since gained acceptance as the theory that helps in undesrtanding the adoption and acceptance of technology utilisation. Davis (1989) integrated the theory of reasoned behaviour in coming up with the TAM theory. TAM is modeled based on end-user bahavioral intentions moreso in agreeing to utilise novel financial technologies. According to Davis (1989), employment and usage of the innovative financial technology has greatly influenced digital financial inclusion. In addition, TAM helps elucidate the reasons for differences in end-users conduct and intents of adopting technology as well predicting the factors driving use and acceptance of technology (Davis, 1989).

Davis (1989) postulates that a positive adoption and usage of technology is positively influenced by the users' need, how the users views the ease in which they can use the technology and their mental reservations in relations to how helpful the technology is. Furthermore, Davis (1989) argues there are two main factors that influences the user intention to employ technology; how the user perceives that technology to be useful and its useableness. It is only after the two factors are present, that the stated technology is accepted and actually used.

TAM has generated critism, inspite of its wide usage, due to its uncertain empirical value and it limits in explaining and explaining powers as well as practicality (Rajak & Shaw, 2021). The theory has been critised for its overly focus on individual user perception without question if techhnology is actually better off (Bagozzi, 2017). Despite the critic, TAM continues to serve as the guide and has been consistently used in investigations that relates to digital financial inclusion (Morkunas, Paschen, & Boon, 2019).

Digital payments and other digital financial inclusion elemnets have to be accepted by the small farming households in Mwea for it to be adopted in their agricultural activities for increased productivity. Acceptance of these digital tools is crucial as they streamline financial transactions, provide access to credit, and offer insurance services, thereby potentially enhancing agricultural activities and overall productivity. Adoption requires farmers to recognize the benefits of digital payments, such as increased convenience, security, and transparency in financial transactions. Additionally, it necessitates overcoming potential barriers like limited digital literacy, concerns about privacy and security, and reliance on traditional financial practices. Through adoption of digital financial inclusion among small farming households in Mwea, the households would experience increased agricultural productivity.

2.3 Empirical Review

The researcher, in this section, reviewed the empirical studies related to digital inclusion and productivity. This was done by doing a review of previous studies similar to the topic of study. The review was based on the variables (digital payments, digital lending and digital insurance) with international and local studies reviewed.

2.3.1 Digital Payments and Agricultural Productivity

Mahakittikun, Suntrayuth and Bhatiasevi (2021) sought to identify the impact of mobile payments on firm performance of retail and services firms in Bangkok, Thailand. The study developed a theoretical model based on the technology, organization and environment framework that included relative advantage, complexity and mobile payment knowledge. Findings of the study indicated that mobile payments positively predict firm performance. This study indicated similar findings to those of Issahaku, Abu and Nkegbe (2018). Issahaku, Abu and Nkegbe (2018) in their study on whether the use of mobile phones by smallholder maize farmers affect productivity in Ghana, found that mobile phone ownership and use significantly improves agricultural productivity. The study found that mobile phone usage positively affected agricultural productivity through the ease of making and receiving payments by farmers.

In China, Su, Peng, Kong and Chen (2021) examined the influence of e-commerce adoption and farmers participation in the digital finance market. The dependent variable, E-commerce adoption was proxies by online purchases and sales measured by engagements in digital payments. Findings from the study indicated that digital payments had a significant and positive effect of farmer’s participation in digital financial markets. This was in turn found to positively influence agricultural productivity.

Some literature, however, show that digital payments have negative or no effect on productivity. For example, Mararo (2018) who investigated the effect of mobile payments on the growth of 100 SMEs in Nakuru town in Kenya established that mobile payments had a positive significant effect on firm growth. However, the study found that mobile payments had no significant effect on the productivity. On their part, Sayid and Omar (2018) investigated the effects of mobile transaction costs on financial performance of SMEs in Mogadishu, Somalia and revealed that mobile money transaction costs affected financial performance of SMEs in Somalia (Sayid & Omar, 2018). The study found that the mobile money transaction costs reduced the productivity and performance of the SMEs indicating a negative effect of digital payments on productivity.

The reviewed studies showed mixed results on the effect of digital payments on productivity. Despite majority of the studies focusing on agricultural productivity some focused on farm productivity which may give a different contextual argument. The studies also focused on either cost with some not majoring on digital payments. Majority of the studies also focused on other economies other than Kenya which indicates research gaps. Hence, the need to investigate the effect of digital payments on agricultural productivity in Kenya with a special focus on Mwea in Kirinyaga county.

2.3.2 Digital Lending and Agricultural Productivity

Literature shows that digital lending influence productivity. some studies show that digital lending improves productivity with others showing that productivity reduced with digital loans. Literature shows that digital financial inclusion provides rural poor households with much needed credit to increase income as well as agricultural productivity. Cong et al (2021) studied financial inclusion in China and whether it had improved input-output efficiency. The study findings showed that the input and output of financial inclusion are generally effective with digital inclusion improving agricultural productivity through digital lending. The study further established that the farmers accessed easy loans digitally. However, the cost of the loans was high for the farmers. The researcher concluded that digital lending had a negative effect on agricultural productivity.

Hu, Liu and Peng (2021) in their study on financial inclusion and agricultural total factor productivity growth in China found that digital financial inclusion had a positive effect on total factor productivity growth. The effect of financial inclusion on total factor productivity growth occurs as a result of providing loans to support production transformation based on specialization and cooperation.

Abayo and Oloko, (2019) who sought to investigate the efffect of M-shwari loan on growth of SMEs in Kisumu Kenya found that mshwari loans had significant effects on firm growth but only if borrowed funds were used in business. The loans increased firm productivity which improved firm growth. However, Issahaku, Abu and Nkegbe (2018) in their study on the use of mobile phones by smallholder maize farmers and its effect on productivity in Ghana established that digital lending reduced productivity among farmers due to high cost of credit which surpassed the benefits from the loan. This indicates that digital lending had a negative effect on agricultural productivity.

The studies show conflicting results on the relationship between digital lending and productivity. This shows that it's not conclusive and so an average reader may not understand how digital lending influence agricultural productivity among small scale farmers. The studies have also shown gaps where their focus is different from the small farmers with the studies done in different localities other than Mwea. This creates the need to investigate the effect of lending on productivity of small farming households within Mwea of Kirinyaga county.

2.3.3 Digital Insurance and Agricultural Productivity

Digital finance thanks to digital savings and insurance products can help in dealing with unexpected expenses. Farmers with access to digital financial services have accessed micro-insurance contracts, which have allowed them to sustain bigger investments earning 16% more than their uninsured peers (World Bank, 2017). Peprah, Koomson, Sebu and Bukari (2020) examined the effects of access to credit, ownership of savings account and insurance product on farmer's productivity and found that financial inclusion had a positive effect on agricultural productivity through insurance products. The study indicated that losses that come with unfavourable conditions and other causes are covered by the insurance products most of which are accessed digitally. This reduces the costs which in turn enhance productivity.

In Tanzania, Tumaini (2019) assessed the impact of savings and credit through mobile money services had any influence on growth of Micro, Small and Medium Enterprises (MSMEs) in the country and found a positive but insignificant relationship between mobile services savings and lending and growth of MSMEs in Tanzania. The study found that the digital insurances products positively affected productivity of the MSMEs through reduced costs in case of losses.

Muzhingi (2022) studied the influence of digital innovation systems on perceived agricultural productivity of Ishamba in Kenya. A telephone interview survey of 77 iShamba customers in Nyeri was undertaken. The sample size for this study was determined using non-probability convenience sampling, and data was input into Microsoft Excel and Google Spreadsheets. Thematic analysis was used to code and analyse the data collected. The study found that insurance offered through digital platforms increase the costs of insurance and negatively influence agricultural productivity.

The studies have majorly focused on organizations other than small scale farmers. The studies have also been done with a focus on growth other than productivity. It was not clear if the findings could be generalized to smallholder farming households in Mwea situation which is the focus of the current study. This shows that research gaps exist which creates the need to investigate the effect of digital insurance on agricultural productivity among small farmers in Kenya and specifically Mwea.

2.4 Summary of Literature Review and Research Gaps

Table 2.1: Summary of Literature Review and Research Gaps

Authors	Jurisdiction	Purpose	Findings	Gaps	Addressing the gap
Mahakittikun, Suntrayuth and Bhatiasevi (2021)	Bangkok, Thailand.	To identify the impact of mobile payments on firm performance of retail and	mobile payments positively affect firm performance	Looked at firm performance Involved retail and services firms	Looked at agricultural productivity Involved small scall farmers in Mwea, Kirinyaga

		services firms			
Su, Peng, Kong and Chen (2021)	China	To examine the influence of e-commerce adoption and farmers participation in the digital finance market	digital payments had a significant and positive effect of farmer's participation in digital financial markets	Used farmer's participation in digital market as dependent	Used agricultural productivity as dependent variable
Mararo (2018)	Kenya	To investigate the effect of mobile payments on the growth of 100 SMEs in Nakuru town	Digital payments had a positive significant effect on firm growth	Looked at firm growth other than agricultural productivity Based on SMEs Done in Nakuru town	Looked at agricultural productivity as the dependent Based on small scale Based the study in Mwea
Cong et al (2021)	China	To establish financial inclusion and whether it had improved input-output efficiency	financial inclusion improves input-output efficiency through digital lending	Looked at input-output efficiency Based in China	Looked at agricultural productivity Done in Mwea, Kenya

Hu, Liu and Peng (2021)	China	To determine the relationship between financial inclusion and agricultural total factor productivity growth in China	digital financial inclusion had a positive effect on total factor productivity growth.	Based in China Involved secondary data	Based in Mwea, Kenya Involved primary data from farmers in Mwea
Abayo and Oloko (2019)	Kenya	To investigate the efffect of M-shwari loan on growth of SMEs in Kisumu Kenya	Mshwari loans had significant effects on firm growth	Looked at Mshwari loans Looked at growth of SMEs in Kisumu	Looked at all digital lending platforms Involved agricultural productivity among small scale farming households in Mwea
Issahaku, Abu and Nkegbe (2018)	Ghana	To establish the use of mobile phones by smallholder maize farmers and	digital lending reduced productivity among farmers due to high cost of credit	Looked at the use of mobile phones Involved maize farmers	Looked at digital financial inclusion Involved all farmers

		its effect on productivity			
Peprah, Koomson, Sebu and Bukari (2020)	Ghana	To examine the effects of access to credit, ownership of savings account and insurance product on farmer's productivity	Financial inclusion enhanced productivity through insurance products	Looked at access to credit, ownership of savings account and insurance product	Looked at financial inclusion
Tumaini (2019)	Tanzania	To assess the impact of savings and credit on growth of Micro, Small and Medium Enterprises	The study found a positive but insignificant relationship	Looked at growth other than productivity Involved Micro, Small and Medium Enterprises	Looked at agricultural productivity Involved small scale farming households
Sayid and Omar (2018) (Sayid & Omar, 2018).	Somalia	To investigate the effects of mobile transaction costs on financial performance of SMEs in	The mobile money transaction costs reduced the productivity and performance of the SMEs	Looked at performance of the SMEs	Looked at agricultural productivity

		Mogadishu, Somalia			

2.5 Conceptual Model

A conceptual model helps the researcher to identify tasks more clearly while developing a clear idea of what is required to be done. It allows readers to quickly get an idea of the study and how the variables relate (Bell, Bryman & Harley, 2022). The current study adopts a conceptual model in which the relationship between digital financial inclusion and productivity is conceptualized. Digital financial inclusion is conceptualized to have an independent empirical role influencing productivity. The operational indicators of digital financial inclusion are: digital payments; digital lending; and digital insurance. Digital financial inclusion has been recognized as a new financial format, which includes three basic business: digital payments, digital investments/insurance and digital financing. Productivity of smallholder farming households is considered as the dependent variable. In a recent study by Fawowe (2020) financial inclusion, irrespective of how it is measured, has positive and statistically significant effect on agricultural productivity. Unlike other previous studies where the role of digital financial inclusion amongst smallholder farming households has been ignored, this model conceptualizes that digital financial inclusion can influence productivity of smallholder farming households. In addition, this study conceptualized digital financial inclusion and productivity which is rare compared to the most common conceptualization of either as access to mobile money and firm growth or broad access to credit on firm performance. Finally, the variables were contextualized from the perspective of smallholder farming households in Mwea, Kirinyaga County, Kenya not like other studies whose context was elsewhere. The proposed study therefore offered significant insights to the relations between the study variables as well as the context. The conceptual model was presented in Figure 2.1.

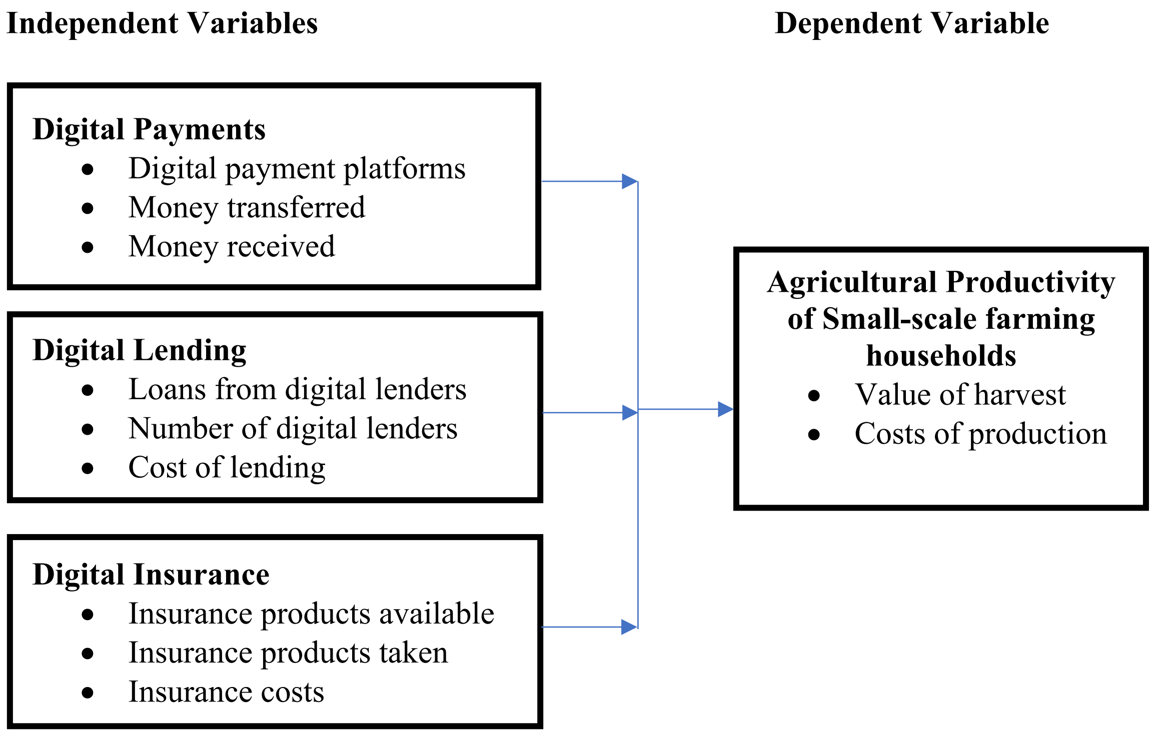

Figure 2.1: Conceptual Model

Source: Researcher (2024)

2.6 Operationalization of Variables

This study adopted digital financial inclusion and agricultural productivity as the variables for the study. Agricultural productivity as the dependent variable was indicated by value of harvest and costs of production. As the independent variable, digital financial inclusion was represented by digital payments, digital lending, and digital insurance. Digital payments were indicated by digital payment platforms as well as amount of money transferred and received. Digital lending was measured in terms of the amount of loans from digital lenders, number of digital lenders and cost of lending. Digital insurance was indicated by insurance costs, digital insurance products available and the insurance products taken by the farmers. The operationalization was shown by Table 2.2.

Table 2.2: Operationalization of Variables

Variable	Constructs	Indicators	Scale of measurement	Sources
Independent	Digital Payments	• digital payment platforms • Money transferred • Money received	Ordinal	Liao, Yao & Hu (2020) Guo, Kong & Wang (2018)
	Digital Lending	• Loans from digital lenders • Number of digital lenders • Cost of digital lending	Ordinal	Alexander & Karametaxas (2021)
	Digital Insurance	• Digital insurance products available • Insurance products taken • Insurance costs	Ordinal	Guo, Kong & Wang (2018)
Dependent Variable	Agricultural Productivity	• Value of harvest • Costs of production	Ordinal	Jayne & Sanchez, 2021).

Source: Researcher (2024)

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

Chapter three is the presentation of the procedure and method that guided the carrying out of this study. In the chapter, the research design and the targeted population in addition to research instruments are discussed. Further, validity and reliability tests are discussed. Finally, the chapter presents the procedures of processing and analysing data.

3.2 Research Philosophy

Research philosophy relates to the development of knowledge and the nature of that knowledge (Bell, Bryman & Harley, 2022). The philosophy underpinning this study is positivism. Positivism assumes in its understanding of the world that the environment and the events of interest are objective, external and independent of the researcher. This philosophy enabled the researcher to come up with objective and independent results on digital financial inclusion and agricultural productivity of households. The researcher did not manipulate the outcomes and presented them as they are based on the collected data. For positivism information is derived from logical and mathematical calculations based on raw data. This made the philosophy relevant as it allowed the researcher to analyse the data statistically to bring out the effect of digital financial inclusion on agricultural productivity of households.

3.3 Research Design

According to Sekaran and Bougie (2016) research design is a plan that lays down the approaches, methods and means of collecting, processing and analyzing information that is suiTable for testing the hypothesized relationships. This study adopted descriptive correlational research design. The design is advantageous as it allows for collection of large amount of data from a sizeable population in a vastly economical manner (Bell, Bryman & Harley, 2022). By using the design, the researcher gained control over the research process and where sampling is used, it is possible to generalize results over the entire population. Furthermore, descriptive correlational research design was considered as being more authoritative and easier to explain and understand (Siedlecki, 2020). The design also allowed the researcher to present the outcomes without manipulation and allowed for the researcher to establish the causeeffect relationship utilizing quantitative and descriptive statistics. Hence, this research design was relevant for this study.

3.4 Target Population

A population is considered to be any group of people, events, or items that are of interest to the researchers that they wish to investigate (Pandey & Pandey, 2021). Target population is a complete set of individuals, cases or objects with some common observable characteristics (Bell, Bryman & Harley, 2022). This study targeted smallscale farming households in Mwea constituency in Kirinyaga county. According to KNBS (2021), Mwea has 7022 farming households. The households formed the unit of analysis from where the sample was got from. The heads of the households formed the respondents for the study hence the unit of observation.

3.5 Sample and Sampling Design

The study sampled 378 households in Mwea. This research sample was determined by the selection of appropriate and accurate number of households using the Yamane sampling formula shown below:

$n = N/\ (1+N\ (e)^2)$

where;

N-population

n-sample

e-margin of error (5% as the population is greater than 1000)

Hence the sample, n $= 7022/\ (1+7022(0.05)^2)$

$=378.4$

$=378$

The study adopted snowballing sampling technique to select the 378 farming households that were considered adequate for the study. In snowball sampling, the research identified intial respondents and asked them help identify other respondents who were actively enganged in small holder farming and are using all the three identified digital financial inclusion proxies.The researcher used the subchiefs and the elders to take them to the small holder farming householders. The researcher used purposive sample to select the head of the household who were involved as the respodent. Purposive sampling enabled the researcher to use their own judgement and knowledge in selecting the respondents for the research.

3.6 Research Quality

To esnure research quality the researcher undertook validity and reliability test. Test of data collection instrument's reliability and validity was done by use of a pilot test. The researcher undertook a pilot test on 38 households in Kirinyaga Central which represented 10% of the sample. Regarding validity, the question items must be sufficient and appropriate in assessing a specific construct through a thorough review of literature and recommendations from the experts (Oyebisi et al., 2018). Validity was achieved by engaging the organization's supervisor and experts to check on research instruments quality and suitability. This enabled the supervisor to identify any gaps that needed amendments in case of any so as to achieve the objective of the study. The supervisor checked and gave reviews on the questions to change or restructure. The recommendations from the supervisor were included the research instrument which enhanced its validity.

The degree upon which data gathering techniques or analysis methods produce consistent results is referred to as data reliability (Bell, Bryman & Harley, 2022). The researcher used the test-retest methodology to test the reliability. Here, the researcher administered the questionnaire a week after the first administration of the questionnaire. This enabled the researcher to compare the results and calculate the Cronbach alpha value which showed the reliability level. A value above 0.7 was obtained indicating a reliable research instrument. The results of the reliability tests is shown in the Table below:

Table 3.1: Reliability Statistics

Item	Cronbach's Alpha	N of Items
Agricultural Productivity	.709	5
Digital Payment	.763	5
Digital Lending	.710	6
Digital Insurance	.811	5

Source: Researcher (2024)

Cronbach's alpha was used to measure internal consistency or reliability of the scale used in the data. Cronbach's alpha coefficient of 0.70 and above indicates that the research instrument is reliable. Where the reliability statistics are below 0.7, there are reliability problems and statements with low alpha value in an objective should be discarded or revised (Gliem & Gliem, 2003). From the findings the variables displayed alpha values of more than 0.7 an indication that the questionnaire was reliable.

3.7 Data Collection Instruments

The study used primary data which entails collection of information for the first time and it was done through the use of structured questionnaires. A questionnaire is a pre-formulated written set of questions to which the respondents record the answers usually within rather closely delineated alternatives. A structured questionnaire was developed with its first part including a list of general questions relating to the household and respondents. In the second part, the researcher had questions relating to digital inclusion with the third section having questions relating to household productivity.

3.8 Data Collection Procedures

The questionnaire was administered by the research with the assistance of research assistants. The research assistants were recruited and trained by the researcher to ensure that they understood what needs to be done which ensured high response rate and collection of necessary data. The questionnaires were administered using the interview method where the researcher/research assistants asked questions and recorded the response on the questionnaire based on the answer from the respondent. This overcame the challenge where the respondents could not understand the questions or could not read and/or write. This also saved on time and enhanced the response rate. The researcher got authorization from the local administration in Mwea which led to smooth data collection within Mwea. The researcher also attached the introduction letter from the university which introduced the researcher to the respondents and made it easy to convince them to provide data.

3.9 Data Analysis Techniques

Once the data was collected, it was cleaned, coded and entered into SPSS version 25 for analysis. The analysis was done by use of descriptive (mean, percentages, frequencies, and standard deviation), correlation analysis, factor analysis and regression statistics. Descriptive statistics was computed to represent general information and respondent's characteristics (Pandey & Pandey, 2021). Correlation was done using Spearman product moment coefficient. Under regression statistics, ordinal regression analysis model was adopted. This enabled the researcher to establish the way digital financial inclusion influence agricultural productivity among small scale farmers in Mwea. The model took the form of:

$$Logit(P(Y \leq i) = \beta_0 + \beta_1 DP_{i2} + \beta_2 DL_{i2} + \beta_3 DI_{i2}$$

Whereby;

Y = the dependent variable is denoting the agricultural productivity of households as measured by the composite value of all statements relating to productivity of households in the questionnaire

β_0= the constant term that depict the level of the agricultural productivity of households when digital payments, digital lending, digital insurance are absent.

DP = the independent variable digital payments as measured by the composite value of all statements relating to digital payments in the questionnaire

DL = the independent variable of digital lending as measured by the composite value of all statements relating to digital lending in the questionnaire

DI = the independent variable of digital insurance as measured by the composite value of all statements relating to digital insurance in the questionnaire

β_1, β_2, β_3 = the beta coefficients denoting the level to which digital payments, digital lending and digital insurance significantly or insignificantly boosts or reduce the level of agricultural productivity of households.

ε = the error term that depict how the data is far or near the regression line.

i =log odds or lags

P=probability

3.10 Ethical Considerations

This research paper made various ethical considerations. First the researcher sought for an authorization letter from the university which assisted in the acquisition of the research permit from NACOSTI. This provided evidence that this was an academic research and the information was used purely for academic purposes only. This gave the respondents the confidence to fill in the questionnaire as requested hence increasing the response rate. The researcher in writing the proposal ensured integrity by paraphrasing, citing, and referencing the sources that the researcher reviewed. The researcher ensured that consent was sought by explaining what the study was all about to the respondents. The researcher allowed the respondents to participate voluntarily in the study without being forced. Confidentiality was ensured by ensuring that the responses were anonymous with no profiling of the respondents.

CHAPTER FOUR:

PRESENTATION OF RESEARCH FINDINGS AND DISCUSSIONS

4.1 Introduction

This chapter presents the findings from the data analyses from the field with statistics generated through SPSS statistical software. The findings are based on the objectives of this study. The main objective of this research was to gauge the influence of digital financial inclusion on productivity of smallholder farming households in Mwea, Kirinyaga County, Kenya. Specifically, the study sought to determine the influence of digital payments on productivity of smallholder farming households; examine the effect of digital lending on productivity of smallholder farming households; and estimate the influence of digital insurance on productivity of smallholder farming households in Mwea, Kirinyaga County, Kenya.

This chapter is based on the following sections; the first section discussed the response rate based on the questionnaire return rate from the field. The second section presents the demographic information relating to the respondents while the third section looks at the descriptive statistics relating to the variables of digital payments, digital lending, digital insurance and agricultural productivity. The fourth and final section presents the regression statistics based on the ordinal regression analysis.

4.2 Response Rate

The study administered a total of 378 questionnaires to farmers in Mwea. From the 378 questionnaires a total of 239 were duly filled and returned for analysis. As a very rough rule of thumb, more than 200 responses provide fairly good accuracy under most assumptions and parameters of a research project. The questionnaire return rate was 63.2% which was good as per Mugenda and Mugenda (2012) who recommended that a response rate of above 60% is good and sufficient for statistical analysis. This shows that the response rate was good for this research. The non-response rate of 36.8% involved the respondents who participated in the pilot study hence not involved in the final research to curb any form of biasness. The non-response also involved the farmers who did not give consent to participate in this research.

4.3 Demographic Information

This section presents the demographic results with reference to number of years in farming, age, gender, share of farming income in the household, and the level of education. The information is based on the respondents of this study. The results are presented in Table 4.1.

Table 4.1: Demographic Information

Demographic Information		**Frequency**	**Percent**	**Cumulative Percent**
Years Involved in Farming	Less than a year	15	6.3	6.3
	1-5 years	27	11.3	17.6
	6-10 years	42	17.6	35.2
	11-15 years	72	30.1	65.3
	15 years and above	83	34.7	100.0
Age	18 - 25 years	16	6.7	6.7
	26 - 33 years	33	13.8	20.5
	34 - 41 years	44	18.4	38.9
	42 - 49 years	64	26.8	65.7
	50 years or above	82	34.3	100.0
Gender	Male	80	33.5	33.5
	Female	159	66.5	100.0
Share of Farming Income	Less than 20%	20	8.4	8.4
	20-40%	31	13.0	21.3
	40-60%	109	45.6	66.9
	More than 60%	79	33.1	100.0

Level of Education	No formal education	75	31.4	31.4
	Primary	94	39.3	70.7
	Secondary	25	10.5	81.2
	College	27	11.3	92.5
	University	18	7.5	100.0
	Total	239	100.0	

Source: Researcher (2024)

From the results presented by Table 4.1, majority of the respondents (64.8%) were involved in farming activities for more than ten years. This was shown by 30.1% of 11-15 years and 34.7% of more than 15 years. Only 35.2% were being involved in farming for less than ten years. This shows that majority of the small-scale farmers in Mwea have been involved in farming for more than ten years. This would enable them to have experienced the fluctuation in agricultural productivity and understand how digital financial inclusion has influenced the productivity of their farms.

On the age, the respondents indicated that 61.1% were aged 41 years and above. Most of the respondents (34.3%) were 50 years and above and 26.8% between 42 and 49 years. However, 38.9% indicated that they were aged 41 years and below. This shows that majority of the small-scale farmers in Mwea are aged above 40 years. This is based on the fact that young people disregard farming and prefer the white-collar jobs in the major towns like Nairobi hence the small number of young people in the small-scale farming.

On the gender, majority of the respondents indicated that they were female (66.5%) while 33.5% indicated that they were female. This indicates that majority of the small-scale farming household heads in Mwea are Male. This is because majority of the land owners in Mwea are men with the women playing a key role in farming within the households. The findings showed that majority of the respondents (78.7%) indicated that farming income contributed more than 40% to the total household income with 45.6% indicating a contribution of 40 to 60% with 33.1% indicating more than 60%. However, 21.3% indicated that farming income contributed less than 40% to the overall household income. This shows that farming is the major source of income for households in Mwea.

On the level of education, 31.4% of the respondents had no formal education. Further, 49.8% indicated their highest education as secondary and below. Only 18.8% had education above the secondary level. This indicates that majority of the small-scale farmers in Mwea had low literacy levels which may create a challenge in the digital financial inclusion for improved agricultural productivity in their farms. A substantial number of the small-scale farmers in Mwea have no formal education.

4.4 Descriptive Statistics

The descriptive results based on the data processed through SPSS that involved the application of statistical tools limited to mean scores and standard deviations are reported in the following subsections. The results describe the digital financial inclusion and productivity of smallholder farming households in Mwea, Kirinyaga County, Kenya. Digital financial inclusion was based on digital payments, lending and insurance among the farming households. The data for analysis for each particular variable was obtained from the Likert scale of measurement that numerically coded the five levels of agreement used. This was supported by open ended questions for every variable.

4.4.1 Digital Payments

Table 4.2 presents findings on the descriptive statistics relating to digital payments among smallholder farmers in Mwea. The findings are based on the level of agreement on statements relating to digital payments.

Table 4.2: Digital Payments

	N	Mean	Std. Deviation	Median
I make payments relating to my farm digitally	239	4.0543	1.24017	5.000
I send a lot of money relating to my farm across digital payment channels	239	3.8641	1.12983	5.000
There are digital payment platforms for small farmers in my area	239	3.8315	.98007	5.000

The cost of digital payments is low compared to traditional forms of payment	239	2.1467	.85263	5.000
I receive payments through digital platforms	239	4.1793	3.95403	5.000

Source: Researcher (2024)

From Table 4.2, the respondents agreed that they received payments through digital platforms as shown by the mean of 4.1793. The respondents further agreed that they made payments relating to their farm digitally shown by mean of 4.0543; they sent a lot of money relating to their farms across digital payment channels shown by mean of 3.8641 and that there were digital payment platforms for small farmers in their area as shown by the mean of 3.8315. However, the respondents disagreed that the cost of digital payments was low compared to traditional forms of payment as shown by the mean of 2.1467. The statements showed a standard deviation of less than 2 indicating that the responses didn't differ much, therefore supporting the mean.

4.4.2 Digital Lending

The study sought to establish the status of digital lending among smallholder farmers in Mwea. This was done through descriptive statistics as shown by Table 4.3.

Table 4.3: Digital Lending

	N	**Mean**	**Std. Deviation**	**Median**
Digital lending platforms in Kenya offer agricultural loans to small scale farmers in my area	239	3.9620	.90757	4.000
I have taken large digital loans to finance my farming activities	239	2.1304	1.15676	2.000
Most of my farming activities are financed through digital loans	239	2.2446	1.16411	2.000
There are many sources of digital lending for farmers in my area	239	3.7609	1.01216	3.500
The cost of digital loans is higher than non-digital loans	239	3.5185	1.08838	3.000

Digital lending boosts financing among small scale farmers	239	3.8152	.96868	4.000

Source: Researcher (2024)

From Table 4.3, the respondents agreed that digital lending platforms in Kenya offered agricultural loans to small scale farmers in their area as shown by the mean of 3.9620. The respondents further agreed that digital lending boosted financing among small scale farmers as shown by mean of 3.8152; there were many sources of digital lending for farmers in their area as shown by the mean of 3.7609; and that the cost of digital loans was higher than non-digital loans as shown by the mean of 3.5185. However, the respondents disagreed that most of their farming activities were financed through digital loans as shown by the mean of 2.2446. They also disagreed that they had taken large digital loans to finance their farming activities as shown by the mean of 2.1304. The statements showed standard deviations of less than 2 indicating that the responses do not differ that much and hence one can make conclusions based on the mean.

4.4.3 Digital Insurance

Table 4.4 presents findings on the descriptive statistics relating to digital insurance among smallholder farmers in Mwea. The findings are based on the level of agreement on statements by the respondents as relates to digital insurance.

Table 4.4: Digital Insurance

	N	**Mean**	**Std. Deviation**	**Median**
I have access to digital insurance services for my farm	239	1.9565	1.44414	1.000
I have taken various insurance products for my crops and farm	239	1.6685	1.04222	1.000
Digital insurance has reduced my insurance costs	239	1.7174	.89719	2.000
Digital insurance products are easy to purchase	239	1.9130	1.06768	2.000
I spend a small amount of money to insure a large value of investment in my farm through digital insurance	239	2.0761	1.13786	2.000

Source: Researcher (2024)

From Table 4.4, the respondents disagreed that they spent a small amount of money to insure a large value of investment in their farm through digital insurance as shown by mean of 2.0761. They also disagreed that they had access to digital insurance services for their farms as shown by mean of 1.9565; digital insurance products were easy to purchase shown by mean of 1.9130; and that digital insurance reduced their insurance costs as shown by the mean of 1.7174. The respondents also disagreed that they had taken various insurance products for their crops and farms as shown by mean of 1.6685. This shows that there is low uptake of digital insurance among smallholder farmers in Mwea. The statements showed standard deviations of less than 2 indicating that the responses do not differ that much and hence one can make conclusions based on the mean.

4.4.4 Agricultural Productivity

Table 4.5 presents findings on the descriptive statistics relating to agricultural productivity among smallholder farmers in Mwea. The findings are based on the level of agreement on statements by the respondents as relates to agricultural productivity.

Table 4.5: Agricultural Productivity

	N	Mean	Std. Deviation	Median
Labour and fertilizers are key expenses to my farm	239	3.7011	.88262	5.000
My farm has a high cost of inputs	239	3.7826	.84058	5.000
My farm experiences high level of productivity	239	2.2283	.94207	2.000
My farm experienced increased harvest in the last year	239	2.3043	.87764	2.000
My farmland is fully used for agricultural production	239	3.6630	.83342	3.500

Source: Researcher (2024)

From Table 4.5, the respondents agreed that their farms had high costs of inputs as shown by the mean of 3.7826. They also agreed that labour and fertilizers were the key expenses to their farms as shown by mean of 3.7011; and that their farmlands were fully used for agricultural production as shown by the mean of 3.6630. However, the respondents disagreed that their farms had experienced increased harvests in the previous years as shown by the mean of 2.3043 and had high value of productivity as shown by the mean of 2.2283. The statements had low standard deviations (less than 2) indicating that conclusions can be made based on the mean of the statements.

The respondents recommended that, in order to enhance agricultural productivity, the government should ensure that there is adequate water supply for the small-scale farmers. The government, through extension officers, should also provide extension services to the farmers especially on the control of pests like snails. The respondents also recommended the provision of cheap inputs like fertilizers and seeds to the farmers for increased agricultural productivity among the farmers. There was need for the government to increase the level of loans to farmers, provide organic fertilizers, install water projects & irrigation services and lower the price of farm inputs. They also recommended that financial institutions diversify their products to farmers in their digital platforms with the government creating a good policy framework that would encourage more financial institutions to extend digital financial services to the farmers. The respondents further recommended the installation of electricity in the smallholder households as well as improving the road network. The farmers also needed to seek for more market information which would influence their productivity.

4.5 Factor Analysis Results

Factor analysis was done to establish the variables extracted from the statements. Factor analysis measures the importance of the variables where items that identified to not to meet objectives are removed and are not included in the final analysis. However, prior to the extraction of the constructs, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and the Bartlett's Test of Sphericity were conducted to determine the appropriateness of the data for factor analysis. A KMO statistic of greater than 0.5, and an associated Bartlett's p-value of less than or equal to 0.05 are required for the data to be sufficient for factor analysis. However, the factor loading should be greater than 0.4.

4.5.1 Factor Analysis for Digital Payment

Table 4.6: Factor Analysis for Digital Payment

Digital Payment	KMO	Bartlett's	Factor loading	Items removed
	0.784	.000		None
DP1			.407	
DP2			.568	
DP3			.921	
DP4			.634	
DP5			.590	

The KMO for digital payment was 0.784 indicating the sample was adequate, while the Barlett's test of sphericity indicated that the items were significant (B=0.000< 0.05). From the results, digital payment statements showed factor loading greater than 0.4 and thus all the five items were retained.

4.5.2 Factor Analysis for Digital Lending

Table 4.7: Factor Analysis for Digital Lending

Digital Lending	KMO	Bartlett's	Factor loading	Items removed
	0.692	.010		None
DL1			.634	
DL2			.790	
DL3			.713	
DL4			.514	
DL5			.757	
DL6			.506	

The KMO for digital lending was 0.692 with Barlett's test of sphericity of 0.010. This shows that the sample was adequate with the digital lending statements being significant. In addition, the factor loadings for the six items on digital lending indicating the sample was adequate, while the Barlett's test of sphericity indicated that the items were significant. From the results, digital lending statements showed factor loading greater than 0.4 and thus all the six items were retained.

4.5.3 Factor Analysis for Digital Insurance

Table 4.8: Factor Analysis for Digital Insurance

Digital Insurance	KMO	Bartlett's	Factor loading	Items removed

	0.803	.000		None
DI1			.541	
DI2			.639	
DI3			.537	
DI4			.750	
DI5			.628	

From the factor analysis, Digital Insurance statements showed a KMO value of 0.803 indicating the sample was adequate. Further, the statements showed a Barlett's test of sphericity value of 0.00 indicating that the items were significant. Further, the six statements had factor loadings of more than 0.4 leading to the decision of retaining of all the items.

4.5.4 Factor Analysis for Agricultural Productivity

Table 4.9: Factor Analysis for Agricultural Productivity

Digital Payment	KMO	Bartlett's	Factor loading	Items removed
	0.649	.001		None
P1			.601	
P2			.737	
P3			.519	
P4			.811	
P5			.526	

The KMO for agricultural productivity was 0.784 indicating the sample was adequate, while the Barlett's test of sphericity indicated that the items were significant ($B=0.001< 0.05$). Based on the findings, the five statements relating to agricultural productivity had factor loadings greater than 0.4. Therefore, all the items were retained.

4.6 Correlation Analysis Results

The researcher undertook a correlation analysis through Pearson product moment coefficient to establish the relationship between digital financial inclusion and agricultural productivity. The relationship is assumed to be significant where the coefficients show pvalues of less than 0.05.

Table 4.10: Correlation Analysis Results

		Agricultural Productivity	Digital Payment	Digital Lending	Digital Insurance
Agricultural Productivity	Pearson Correlation	1			
	Sig. (2-tailed)				
	N	184			
Digital Payment	Pearson Correlation	.427**	1		
	Sig. (2-tailed)	.000			
	N	184	184		
Digital Lending	Pearson Correlation	.198**	.083	1	
	Sig. (2-tailed)	.007	.260		
	N	184	184	184	
Digital Insurance	Pearson Correlation	.355**	.097	.069	1
	Sig. (2-tailed)	.000	.191	.351	
	N	184	184	184	184

Source: Researcher (2024)

From the correlation analysis results, the digital financial inclusion factors showed correlation coefficients with p-values of less than 0.05. This indicates that digital payment, digital lending and digital insurance had a significant relationship with agricultural productivity. The coefficients were positive indicating that digital payment, digital lending and digital insurance had a significant relationship with agricultural productivity of small-scale farmers in Mwea.

4.7 Regression Analysis Results

The researcher sought to establish the influence of digital financial inclusion on productivity of smallholder farming households in Mwea, Kirinyaga County, Kenya. This was done by undertaking regression analysis based on an ordinal regression model. The results are presented in the following subsections.

Table 4.11: Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	412.623			
Final	403.158	59.465	8	.000
Link function: Logit.				

Source: Researcher (2024)

The Chi square (59.465) has a pvalue of 0.000 which was less than 0.05. This shows that there was a significant improvement in the fit of the final model as compared to the null model, hence, the model shows a good fit to the data.

Table 4.12: Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	67.187	88	.952
Deviance	55.422	88	.997

Link function: Logit.

Source: Researcher (2024)

The goodness of fit Table shows the measurement of how well the observed data correspond to the fitted or assumed model. As per the results, the values show pvalues of above 0.05 indicating that they were insignificant. This means that there are no significant differences in the observed data and the fitted (assumed) model

Table 4.13: Pseudo R-Square

	R-Square
Cox and Snell	.046
Nagelkerke	.066
McFadden	.040

Link function: Logit.

Source: Researcher (2024)

Model shows the Pseudo R-Square with Pseudo meaning that it is not technically explaining the variation. However, the values can be used to approximate the variation in the criterion variable. In ordinal regression, we use McFadden value of R-Square. In this case we can say that there has been a 4% improvement in the prediction of the outcome (agricultural productivity) based on the predictors (digital payment, lending and insurance) in comparison to the null model (when there are no predictors).

Table 4.14: Parameter Estimates

	Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound

Threshold	[Y = 2.00]	-2.771	3.048	.826	1	.363	-8.745	3.203
	[Y = 3.00]	2.496	3.046	.671	1	.413	-3.474	8.467
Location	AGE	.068	.147	.215	1	.643	-.219	.355
	GN	-.330	.385	.737	1	.391	-1.084	.424
	[X1=1.00]	-3.337	1.358	6.041	1	.014	-5.998	-.676
	[X1=2.00]	-.143	.438	.107	1	.744	-1.001	.715
	[X1=3.00]	0[a]	.	.	0	.	.	.
	[X2=1.00]	-.870	2.126	.167	1	.683	-5.038	3.298
	[X2=2.00]	.132	.451	.086	1	.770	-.753	1.017
	[X2=3.00]	0[a]	.	.	0	.	.	.
	[X3=3.00]	.180	2.994	.004	1	.952	-5.688	6.047
	[X3=4.00]	1.332	2.957	.203	1	.652	-4.464	7.128
	[X3=5.00]	0[a]	.	.	0	.	.	.

Link function: Logit.
a. This parameter is set to zero because it is redundant.

Source: Researcher (2024)

Estimates shows the probability of a case falling above a given category on the dependent variable. The sign on the estimates is interpreted similar to the linear regression. A positive estimate shows an increase in the likelihood of the case falling into a higher category of dependent variable. However, a negative estimate shows an increase in the likelihood of the case falling into a lower category of dependent variable. Age shows an estimate of 0.068 indicating that increased age means an increased chance of falling into the higher category of agricultural productivity. This shows that there is a positive relationship between age and agricultural productivity. For gender, farmers who are of the male gender have a lower chance of falling into higher category of agricultural productivity. This is shown by the negative estimate (-.330). Hence, gender has a negative relationship with agricultural productivity.

For digital payments, the estimate is -3.337 [X1=1.00]. This shows that farmers who adopt digital payments have a higher productivity compared to those that do not adopt digital payment in their agricultural activities. As for digital lending, those farmers who have little usage of digital lending in their agricultural activities have lower productivity levels compared to those who highly adopt digital lending in their farming activities. For digital insurance (X3), the lower level of digital insurance shows positive sign against productivity indicating that digital insurance positively influence productivity. This is confirmed by a higher figure in the second category which shows that increased digital insurance increases the chances of increased agricultural productivity.

Table 4.15: Odds ratio

		Estimate	OR (exp())
Location	AGE	0.068	1.070
	GN	-0.330	0.719
	[X1=1.00]	-3.337	0.036
	[X1=2.00]	-0.143	0.867
	[X1=3.00]	0[a]	
	[X2=1.00]	-0.870	0.419
	[X2=2.00]	0.132	1.141
	[X2=3.00]	0[a]	
	[X3=3.00]	0.180	1.197
	[X3=4.00]	1.332	3.788
	[X3=5.00]	0[a]	

Source: Researcher (2023)

Odds ratio represents the odds of falling into a higher or lower category of the dependent variable with a unit change in the independent variable. If the odds ratio is greater than 1, then there are increasing odds of being in higher category with a unit increase in the predictor variable. Age shows an odds ratio of 1.070. The odds of higher productivity are 1.07 times higher for higher aged farmers. Therefore, with an increasing age among the smallholder farmers, there are higher chances of high agricultural productivity among the farmers. Similarly, digital insurance (X3) had an odds ratio of 1.197 OR> 1. This shows that the odds are 1.197 times higher for those with digital insurance. This shows that where the smallholder farmers increase their adoption of digital insurance in their farms, there are high chances that the agricultural productivity would increase.

On the other hand, where the odds ratio is less than 1, then there are decreasing odds of being in higher category with a unit increase in the predictor variable. From the results, being a male reduces the chances of increasing agricultural productivity (OR=0.719). This shows that the odds of higher agricultural productivity are 0.719 times less where the farmers are male. Digital payments (X1) had odds of 0.036 for the low digital payment category which is less than 1 and showing that the odds for higher productivity were 0.036 less for those who made fewer digital payments for their agricultural activities compared to those who made more digital payments. This shows that agricultural productivity would increase as the adoption of digital payments among the farmers increase showing that the productivity of the small-scale farming households increases with digital payments. Additionally, digital lending (X2) shows odds 0.419 for higher productivity indicating low odds for low digital lending and higher odds for farmers with high digital lending levels (1.14). The estimates turn positive with increased digital lending showing that the odds increase with digital lending. This shows there are increasing odds that increased digital lending would lead to increase agricultural productivity among small scale farming households. This depicts that increased digital lending increases agricultural productivity among the smallholder farmers. There are higher chances of increased productivity when the farmers increase digital lending for their farming activities.

Table 4.16: Test of parallel lines

Test of Parallel Lines[a]

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	79.956			
General	75.402	4.554	7	.714

The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.
a. Link function: Logit.

Source: Researcher (2024)

The test of parallel lines is an assumption of the ordinal regression model. It assumes that the effects of any predictor variables are consistent or proportional across the different thresholds of the dependent variables. The odds of predictor variable falling into a higher category of the dependent variable are the same as the odds of falling into a lower category. The pvalue is greater than 0.05 indicating that the assumption of parallel lines was met. This shows that the probability of falling into higher odds varies across categories of agricultural productivity for digital financial inclusion.

CHAPTER FIVE

SUMMARY OF DISCUSSIONS, CONCLUSIONS, AND RECOMMENDATIONS

5.1 Introduction

This chapter summarizes the discussion of the statistical findings from the influence of digital financial inclusion on productivity of smallholder farming households in Mwea, Kirinyaga County, Kenya. The chapter then gives a conclusion from the research findings and closes with the proposed recommendations based on the conclusions.

5.2 Summary of Discussion of Findings

This section is a summary of the findings based on the objectives of the study. This enables the reader to get a glimpse of the findings without going through the statistical analysis.

5.2.1 Influence of digital payments on productivity of smallholder farming households in Mwea, Kirinyaga County, Kenya

In the first objective, the study sought to determine the influence of digital payments on productivity of smallholder farming households in Mwea, Kirinyaga County, Kenya. From the descriptive statistics, the findings show that there were various digital payment platforms available for small-scale farmers. Further, the households seemed to have received and made payments relating to their farms digitally. The participants indicated that they had sent a lot of money relating to their farms across digital payment channels. However, the findings showed that the cost of digital payments was not low compared to traditional forms of payment.

From the regression analysis, the findings showed that digital payment had a positive effect on agricultural productivity of the selected households. This was shown by the increasing odds for higher outcome due to increased digital payments. The findings are in line with those of Issahaku, Abu and Nkegbe (2018) who found that mobile phone usage positively affected agricultural productivity through the ease of making and receiving payments by farmers. However, the findings differ with those of Sayid and Omar (2018) who found that the digital payment transaction costs reduced the productivity indicating that a negative effect existed between digital payment and productivity.

5.2.2 Effect of digital lending on productivity of smallholder farming households in Mwea, Kirinyaga County, Kenya

In the second objective, the study sought to examine effect of digital lending on productivity of smallholder farming households in Mwea, Kirinyaga County, Kenya. This was addressed by undertaking descriptive and regression analysis. From the descriptive analysis, the study found that there were many sources of digital lending for farmers in the selected area. It was also established that digital lending platforms in Kenya offered agricultural loans to small scale farmers which boosted their financing despite the cost of digital loans being higher than non-digital loans. However, the digital loans financed only a small percentage of the agricultural activities among the farmers who took small digital loans for farming.

From the regression statistics, the findings showed that the odds of higher agricultural productivity increased with digital lending. This shows that digital lending had a positive effect on agricultural productivity. Therefore, increased digital lending leads to increased agricultural productivity. The findings are similar to those of Abayo and Oloko (2019) who established that digital loans increased firm productivity. However, the findings differ with those of Cong et al (2021) who established that digital lending had a negative effect on agricultural productivity.

5.2.3 Influence of digital insurance on productivity of smallholder farming households in Mwea, Kirinyaga County, Kenya.

In the third objective, the study sought to estimate the influence of digital insurance on productivity of smallholder farming households in Mwea, Kirinyaga County, Kenya. The findings were generated through descriptive and regression analysis. From the descriptive results, the findings showed that there was low uptake of digital insurance for crops and farms. This was due to limited access of the services as well as the complexity in the purchase of digital insurance by the small-scale farmers. For the households that took digital insurance, they neither experienced reduction in insurance costs nor invested a small amount to insure a large agricultural investment. This shows that there is low uptake of digital insurance among smallholder farmers in Mwea.

From the regression analysis based on ordinal regression model, the findings showed that there were higher odds of higher agricultural productivity when digital insurance was adopted. This was shown by the odds for those who adopted low digital insurance with those that adopted higher levels of digital insurance showing higher odds. Peprah, Koomson, Sebu and Bukari (2020) who found that digital insurance had a positive effect on agricultural productivity. This was also in line with those of Tumaini (2019) who found that digital insurances products positively affected productivity. The findings, however, differ with those of Muzhingi (2022) who found that insurance offered through digital platforms negatively influence agricultural productivity.

5.3 Conclusions

In line with the first objective, the findings showed that digital payments were made but the costs were high in comparison to the traditional forms of payment. This leads to the conclusion that smallholder farming households in Mwea adopt digital platforms in making and receiving payment for their agricultural activities. The results also showed that digital payment had a positive effect on the agricultural productivity. This study, therefore, concludes that digital payment had a positive effect on the productivity of smallholder farming households in Mwea, Kirinyaga County, Kenya. This shows that increased digital payments among the smallholder farming households in Mwea would lead to increased agricultural productivity among the households.

As per the second objective, the results showed that despite the existence of various digital lending platforms, the uptake was low with the farmers taking small amounts of digital loans due to cost. This study, hence, concludes that there is low uptake of digital lending among smallholder farming households in Mwea, Kirinyaga County, Kenya. From the regression, digital lending showed a positive effect on agricultural productivity. This study, therefore, concludes that digital lending positively affects the productivity of smallholder farming households in Mwea, Kirinyaga County, Kenya.

In the third objective, the findings showed that the findings showed that there was low uptake of digital insurance for crops and farms. The digital insurance also led to increased insurance costs. This study concludes that the uptake of digital insurance is low among smallholder farming households in Mwea, Kirinyaga County, Kenya. The findings also showed that digital insurance had a positive effect on agricultural productivity. This leads to the conclusion that digital lending has a positive effect on productivity of smallholder farming households in Mwea, Kirinyaga County, Kenya.

5.4 Recommendations

5.4.1 Policy Makers

The findings of the study recommend for the policy formulators in the agricultural sector to formulate appropriate regulations and standards encouraging to fully adopt the usage of digital financial platforms for increased financial inclusion among smallholder farming households in Kenya. This is because digital financial platforms have become essential in financial inclusion in the agricultural sectors. Moreover, they should also formulate policies that involve the increased access of digital financial channels by smallholder farming households for increased agricultural productivity among the households.

5.4.2 Smallholder Farming Households

For the smallholder farming households, there is need for them to increase their uptake of the digital payment for them to experience an increased agricultural productivity. This can be done by increase their usage of digital payments in their agricultural activities. They can send money to suppliers and receive money from buyers through their mobile phones or banks other than cash. This would enable them to reduce the time spent in physically sending or receiving money as well as the risk and cost involved. They also need to borrow more loans digitally as it would lead to increased agricultural productivity. This would enable them to pay for inputs to boost productivity and repay after harvest. They also ought to take digital insurance which would protect them from unexpected losses in their farms. This would increase the productivity of their farms as the findings showed that digital insurance positively influences agricultural productivity. Generally, the households need to adopt digital financial channels which would increase their financial inclusion for increased agricultural productivity.

5.4.3 Areas for Further Research

This study recommends that other researchers adopt different measures of digital financial inclusion and agricultural productivity in future studies. Other researchers should undertake a similar study based in another county other than Kirinyaga for comparison of results. The researchers should also undertake a similar research based on other influencers of productivity of smallholder farming households in Mwea.

Large other than smallholders' households can be used in future studies for comparison of results.

5.5 Limitations of the Study

The study faced a number of limitations. First, the study was limited to small farming households in Mwea. Other farmers and localities were not included which limited the generalizability of the study findings. Secondly, the study was limited to digital financial inclusion and agricultural productivity. Other factors influencing agricultural productivity were left out. Further, the measures adopted on digital financial inclusion and agricultural productivity also created a limitation to the study.

In addition, the study was limited by the unwillingness of the respondents to provide information required for the research. This was based on the fear that the information may be misused. The respondents were assured that the data would be purely used for academic purposes. The study was also limited by the research methodologies which may limit the generalizability of the findings. This was overcome by making recommendations for further research.

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APPENDICES

APPENDIX I: INTRODUCTION LETTER

Dear Respondent:

I am a post graduate student undertaking a Master in Management of Agribusiness (MMA) at Strathmore University. I am carrying out a study on INFLUENCE OF DIGITAL FINANCIAL INCLUSION ON PRODUCTIVITY OF SMALLHOLDER FARMING HOUSEHOLDS IN MWEA, KIRINYAGA COUNTY, KENYA.

I am requesting you to participate in this study by providing answers to the questions in the questionnaire. The data provided will be confidential and purely used for this study.

Your participation will be highly appreciated.

David Mukaru

APPENDIX II: QUESTIONNAIRE

This questionnaire seeks information on **the influence of intrinsic motivation of employee performance of public organizations in Kenya**. The study hopes to obtain the required data through filling out the questionnaire by ticking in the answer box that goes with your choice. For confidentiality purposes do not indicate your name or that of the organization.

Section A: Demographic Information

Tick where appropriate

1. For how have you been undertaking farming activities? **(Please tick one)**

Less than a year [ ] 1-5 years [ ] 6-10 years [ ] 11-15 years [ ]

15 years and above [ ]

2. What is your age bracket? **(Please tick one)**

18 - 25 years [ ] 26 - 33 years [ ] 34 - 41 years [ ] 42 - 49 years [ ]

50 years or above [ ]

3. What is your gender?

Male [ ] Female [ ]

4. What is the share of the income from farming in your household income?

less than 20% [ ]

20-40% [ ]

40-60% [ ]

More than 60% [ ]

5. What is your level of education?

No formal education [ ]

Primary [ ]

Secondary [ ]

College [ ]

University [ ]

Section B: Financial Inclusion

6. To what extent do you agree with the following statements related to digital payments, digital lending and digital insurance as elements of digital financial inclusion for your farming? Please indicate the extent to which you agree or disagree with each of the statements. **(Scale: 1. Strongly Disagree 2. Disagree 3. Neutral 4. Agree 5. Strongly agree)**

Statement	(1)	(2)	(3)	(4)	(5)
Digital Payments					
I make payments relating to my farm digitally		4		4	
I send a lot of money relating to my farm across digital payment channels		2			
There are digital payment platforms for small farmers in my area		4		4	
The cost of digital payments if low compared to traditional forms of payment		2			
I receive payments through digital platforms		4			
Digital Lending					
Digital lending platforms in Kenya offer agricultural loans to small scale farmers in my area		4			
I have taken large digital loans to finance my farming activities		2			
Most of my farming activities are financed through digital loans		2			
There are many sources of digital lending for farmers in my area		2			

The cost of digital loans is higher than non-digital loans		4			
Digital lending boosts financing among small scale farmers		2			
Digital Insurance					
I have access to digital insurance services for my farm		2			
I have taken various insurance products for my crops and farm		2			
Digital insurance has reduced my insurance costs		2			
Digital insurance products are easy to purchase		2			
I spend a small amount of money to insure a large value of investment in my farm through digital insurance		2			

7. Which other digital financial inclusion measures are used by the small-scale farmers within your area?

Section C: Agricultural Productivity of Households

8. To what extent do you agree with the following statements related to farming productivity of your household? Please indicate the extent to which you agree or disagree with each of the statements. **(Scale: 1. Strongly Disagree 2. Disagree 3. Neutral 4. Agree 5. Strongly agree)**

Statement	(1)	(2)	(3)	(4)	(5)
Labour and fertilizers are key expenses to my farm		4			
My farm has a high cost of inputs		4			

My farm experiences high level of output		2			
My farm experienced increased harvest in the last year		2			
My farmland is fully used for agricultural production		4			

9. What should be done to enhance agricultural productivity among small scale farmers in your area?

____

____

____

Thank You

APPENDIX III: NACOSTI RESEARCH PERMIT

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Ref No: 905733

Date of Issue: 25/April/2023

RESEARCH LICENSE

This is to Certify that Mr.. David Mukaru of Strathmore University, has been licensed to conduct research as per the provision of the Science, Technology and Innovation Act, 2013 (Rev.2014) in Kirinyaga on the topic: Influence of Digital Financial Inclusion on Productivity of Smallholder Farming Households in Mwea, Kirinyaga County, Kenya for the period ending : 25/April/2024.

License No: **NACOSTI/P/23/25250**

905733

Applicant Identification Number

Director General
NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Verification QR Code

NOTE: This is a computer generated License. To verify the authenticity of this document, Scan the QR Code using QR scanner application.

See overleaf for conditions

APPENDIX IV: ETHICAL APPROVAL LETTER

Strathmore
UNIVERSITY

29th March 2023

Mr Mukaru David,
mukarudavid@gmail.com

Dear Mr Mukaru,

RE: Influence of Digital Financial Inclusion on Productivity of Smallholder Farming Households in Mwea, Kirinyaga County, Kenya

This is to inform you that SU-ISERC has reviewed and **approved** your above **SU- master's** research proposal. Your application reference number is **SU-ISERC1647/23**. The approval period is from **29th March 2023 to 28th March 2024**.

This approval is subject to compliance with the following requirements:

i. Only approved documents including (informed consents, study instruments, and MTA) will be used
ii. All changes including (amendments, deviations, and violations) are submitted for review and approval by SU-ISERC.
iii. Death and life-threatening problems and serious adverse events or unexpected adverse events whether related or unrelated to the study must be reported to SU-ISERC within 48 hours of notification
iv. Any changes, anticipated or otherwise, that may increase the risks or affect the safety or welfare of study participants and others or affect the integrity of the research must be reported to SU-ISERC within 48 hours
v. Clearance for the export of biological specimens must be obtained from relevant institutions.
vi. Submission of a request for renewal of approval at least 60 days prior to the expiry of the approval period. Attach a comprehensive progress report to support the renewal.
vii. Submission of an executive summary report within 90 days of completion of the study to SU-ISERC.

Before commencing your study, you will be expected to obtain a research license from National Commission for Science, Technology, and Innovation (NACOSTI) https://research-portal.nacosti.go.ke/ and obtain other clearances needed.

Yours sincerely,

for: **Dr Ben Ngoye,**
Secretary; SU-ISERC

Cc: Mr Ambrose Rachier,
Chairperson; SU-ISERC

STRATHMORE UNIVERSITY INSTITUTIONAL SCIENTIFIC AND ETHICAL REVIEW COMMITTEE
(SU-ISERC)
29-Mar-2023
Email:ethicsreview@strathmore.edu
P.O BOX 59857-00200
NAIROBI-KENYA

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