AN ASSESSMENT OF THE EFFECT OF AGRICULTURE AUTOMATION ON EMPLOYMENT IN SELECTED PARTS OF CENTRAL PROVINCE, ZAMBIA

BY

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A Dissertation submitted to the University of Zambia in partial fulfilment for the Awarding of the Master of Science in Human Resource Management

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DECLARATION

I, Chibuye Dorica Sitali do hereby declare that this work is my original work achieved through personal reading and research. This work has never been submitted to the University of Zambia or any other universities. All sources of data used and literature on related works previously done by others, used in the production of this dissertation have been dully acknowledged. If any omission has been made, it is not by choice but by error.

Signature…  ……Date: 11 May 2023… ……

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APPROVAL

This Dissertation by Chibuye Dorica Sitali is approved as fulfilling the requirements for the award of a Degree of Master of Science in Human Resource Management.

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ABSTRACT

There are about 400 Commercial farmers in Zambia and several of them are located in Mkushi and Chisamba Districts, and farmers are increasingly adopting use of automated equipment to increase farm yields. However, use of automated equipment threatens job security of farm employees. Currently, it is not well documented how the adoption of automated farming is affecting employees in Zambia. Hence, the study assessed the effect of automation in the agriculture sector on employment in Chisamba and Mkushi Districts of Central Province by; (a) establishing kinds of automation used; (b) ascertaining levels/types of skills affected by automation; and (c) proposing measures to reduce effects of unemployment in the agriculture sector due to automation. It was a mixed method approach and Survey design involving 138 commercial farmers which were randomly selected using simple random technique. A semi-structured questionnaire was setup on Google platform and a link was generated. The link was sent to all commercial farmers through emails and short messages service (SMS). The data collection tool was semi-structured. The data was analysed using Statistical Package for Social Sciences (SPSS) version 14 and the opened-ended responses were analysed thematically. The study found that, (a) most farmers in Mkushi and Chisamba use automated devices to farm, and these include both heavy and light equipment; (b) the growing use of automation in agriculture made one-third of unskilled employees lose employment, though blending of traditional and automated farming is currently an option; and (c) labour laws threaten employment in agriculture in favour of automated agriculture. Implying automation has a negative effect on employment security of unskilled labour force in the sector, statutory labour obligations that farmer employment must meet is pushing farmers to opt for automated agriculture, though blending manual labour and automation is a growing option. Therefore, the Ministry of Labour and Social Security (MLSS) and National Pension Scheme Authority (NAPSA) to find a win-win situation of engaging commercial farmers in meeting statutory obligations for their employees; farm employees must be empowered and provided with skills development, and the Ministry of Finance and National Planning (MoFNP) and Ministry of Commerce and Industries (MCI) should restrict imports of locally produced products to save local employment. Future studies must establish the effects of job losses due to automation on commercial farm employees.

Key Terms: Effect, Automation, Employment, Zambia, Agriculture Sector

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DEDICATION

This Research is dedicated to my father Dr. Joseph Lubinda Sitali who encouraged me to pursue my Master's Degree and continuously encourages me to never stop learning and improving myself. To my husband Dinko Svetic, thank you for your all your support, for being there whenever I needed to attend to studies and for always believing in me. To my little sunshine Elena Mumbi Svetic, thank you for allowing Mummy to pursue her studies.

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LIST OF ACRONYMS AND ABBREVIATIONS

BA:	Bachelor of Arts
BSc:	Bachelor of Science
MoU:	Memorandum of Understanding
NAPSA:	National Pension Scheme Authority
SSA:	Sub-Sahara Africa
USD:	United States Dollar

CHAPTER 1

INTRODUCTION

1.0 Overview

The chapter presents the background of the study topic area. The background contains the statement of the problem, aim of the study, study objectives, questions, conceptual framework, significance of the study, scope of the study, definition of the key terms and the chapter summary.

1.1 Background of the study

Automation is technology that assists humans, with limited guidance, in the production, maintenance, or delivery of products or services. Automation technology also autonomously produces, maintains, or delivers those products or services. The definition encompasses a large number of applications, from physical robots programmed to do manual tasks (Murphy, 2020). The concern in the first definition of automation is that it is works without continuous human guidance because it is a self-learning system capable of making decisions without human. This concerns human resource practitioners and academicians in developing countries where employment is largely labour intensive especially in the agriculture sector. Concern is on the threat of automation on employment security especially among highly illiterate farm workers and smallholders with digital divide and limited income opportunities. Thus, the study was conducted to establish the effect of automation on employment in the Zambian Agriculture Sector. The chapter described the background to the automation, and agriculture, statement of the problem, purpose of the study, objectives and questions of the study, hypothesis, definition of key terms of operation, structure of the dissertation, and summary of the chapter.

Agriculture has relatively transformed from labour intensive to mechanised intensive industry in the last century. The mechanisation of agriculture is disproportionally applied in the developed countries as opposed to the developing countries (Marinoudi et al., 2019). However, the developing countries' agriculture sector is likely to be transformed at a rapid pace than the developed countries acquired it because of marketing forces. It is the scale at which the scale and pace that the transformation is taking place that is despairing the human capital in developing countries (Liu, 2020). The pace is likely to render many people that depend on the industry unemployed especially that the manufacturing sector is small and requires skilled labour and it is equally embracing automation.

In over the last 15 years, the agricultural industry has started to digitise (Liu, 2020). Through this transformation there was a continuous labour outflow from agriculture, mainly from standardised tasks within production process. Robots and artificial intelligence can now be used to conduct non-standardised tasks which include among other tasks fruit picking, selective weeding, crop sensing (Guzueva et al., 2020). These tasks were previously done by human workforce despite the automation of the agriculture sector.

This trajectory is also applied to ploughing and combine harvesting among other tasks (Gaus and Hoxtel, 2020). Despite the advancements to automatise the agriculture industry, there is an assumption that augmentation of the agricultural roles played by automation will not replace the critical roles that humans play in the agriculture production (Liu, 2020). Automation and robots in many instances will

work collaboratively with humans. Arguably, the sophisticated automation such as new robotic ecosystem creates complex ethical, legislative and social effects (Liu, 2020; Lima et al., 2021).

However, the benefits of automation cannot be underestimated because they are there to be seen such as increased production levels, improved quality and reliability, reduced production costs, and reduction of waste (Mukhalipi, 2018). On the other hand, while automation improves efficiency and increases productivity, it is feared that it also increases unemployment on a large scale.

In Zambia, like many other developing countries it has been observed that automation in the agriculture sector might disrupt economic and social activities in less than six years times (Mukhalipi, 2018). Little is known about the margin by which poverty levels would be reduced both in rural and urban areas by using technological advancements and automation in the agriculture sector. Human capital in Zambia is largely void of literacy and skills in information, communication, and technology to easily embrace automation in the agriculture sector. Attempts are steadily increasing in Zambia to spread the automation of the agriculture sector due to its high yield benefits and food security despite the acknowledgment that it rapidly creates massive unemployment (Adu-Baffour, Daum and Birner, 2019; Daum and Heni, 2020).

The most used automation type in Zambia is irrigation at both the large scale and small scale. The large commercial farmers use the most sophisticated. There is no evidence available yet to state how the irrigation automation replaced human labour. There is still a strong relationship between large commercial farmers and out growers in different sectors of the agriculture industry, such as the cotton sector. Some work as out growers, and some are in engaged in harvesting despite the growing use of automated combine harvesters (Adu-Baffour, Daum and Birner, 2019). There is no clear picture of the effect of automation on replacement of human labour. Though it is evident that there is an increasing marketing trend of cultivators or trailers, and tractors. These have targeted the small farmers with the aim of modernising their cultivation. There is need to establish the adaption to automation and its effect on human labour.

Digitalisation is a rapid growing of automation and it has been championed in Zambia (Advisors, 2019). Though there are limited studies to substantiate its effects on improving agriculture in Zambia. Recently, about five years ago, Zambia entered into a memorandum of understanding (MoU) to scale-up digitalisation of agriculture and education. The MoU was signed with the Southern Africa Telecentre Network. The investment estimated at United States Dollars (USD) 650,000 was meant for information Communication technology to improve agricultural educational among rural farmers. The education would be shared through mobile phones and internet on weather, and prices of commodities. Interventions such as this one, is not an immediate threat to human labour in agriculture, instead they offer invaluable skills for improving agriculture and diversification through value chain. This could also be a pathway to managing the effects of automation when that is the case (Advisors, 2019).

Chisamba is one of the most lucrative agriculture regions characterised by both commercial and smallholder farmers. The district is known for their agricultural activities. For example, Chisamba has over 32, 000 small scale farming households and 256 commercial farmers. Mkushi is known for its large commercial agricultural operations and hosts a substantial community of expatriate farmers. Most of these are white Zambian farmers. In both districts Farming activities are blended with automation and labour-intensive practices. The two districts were selected because they would provide required knowledge on the effect of automation on agriculture the agriculture sector (Daum and Heni, 2020).

1.2 Statement of the Problem

The agriculture sector in Zambia is largely labour intensive and employs over 60% of the population (Statistics Agency, 2018). It provides informal social security to mostly rural residents (Adu-Baffour, Daum and Birner, 2019; Daum and Heni, 2020) and young people engaging in agribusiness (Djurfeldt and Hillbom., 2016). The potential of Zambia becoming a regional food harbour in the region is inevitable and using automated production would hasten it but at the expense of creating unemployment. Automation of the agriculture sector is already taking shape among the commercial and cooperative farmers. The effects of automation on the agriculture sector in relation to creating unemployment in Zambia have been predicted, however, not empirically established based on primary data (Mukhalipi, 2018). It is with that background that this study delved to establish the effect of automation on employment in the Zambian agriculture sector, a case study of Chisamba and Mkushi Districts of Central Province in Zambia. This would provide an empirical insight for human resource practice and academic engagement to find solutions to safeguard intensive labour in the short and long term.

1.3 Aim of the study

The aim of this study is to assess the effect of automation in the agriculture sector on employment in Chisamba and Mkushi Districts of Central Province.

1.3.1 Study objectives

To achieve the above aim, the following objectives were framed:

- To establish the kinds of automation used in the agriculture sector in Chisamba and Mkushi Districts.
- To ascertain the levels/types of skills affected by automation in the agriculture sector in Chisamba and Mkushi Districts.
- To assess the effect that automation has brought on employment in Chisamba and Mkushi Districts.
- To propose measures of reducing the effects of unemployment in the agriculture sector due to automation in Chisamba and Mkushi Districts

1.3.2 Research Questions

- What are the kinds of automation used in the agriculture sector in Chisamba and Mkushi Districts?
- What are the levels/types of skills affected by automation in the agriculture sector in Chisamba and Mkushi Districts?
- What is the effect that automation has brought on employment in Chisamba and Mkushi Districts?
- What are the measures of reducing effect of unemployment in the agriculture sector due to automation in Chisamba and Mkushi Districts?

1.4 Conceptual framework

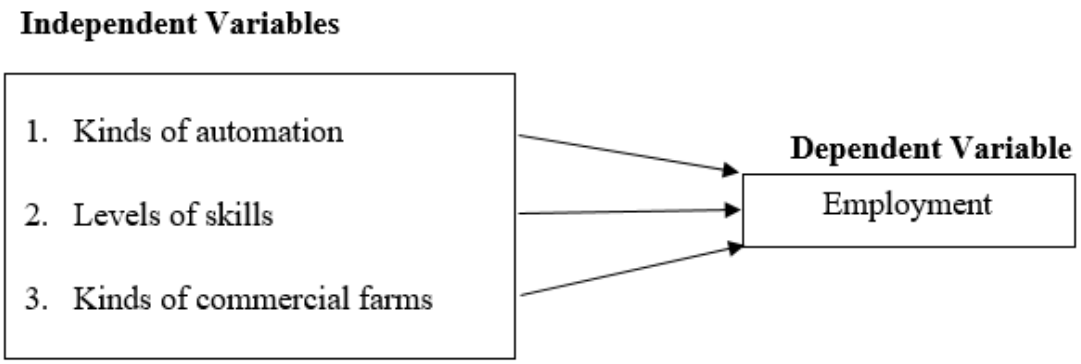


FIGURE 1: IMPACT OF AUTOMATION ON EMPLOYMENT FRAMEWORK

Figure 1 presents the conceptual framework which was constructed based on the study objectives. It represents a linear relationship between the independent variables on the left and the dependent variable on the right side. This is the relation of association that was tested using the study hypothesis. As explained in the theoretical framework, human capital development is skilled and unskilled which is common in commercials farms. It is also common in commercial farms that to increase productivity, automation would be used, and this can either be used in a blended manner or replace human labour. The dependent variable is employment, which is a state or being employed or unemployed, since the hypothesis would be tested it would show whether automation replaces human labour and among and the kind of farms that use it and the kinds of automation that is used.

1.5 Significance of the study

The study findings are very important to policy makers. The findings will assist policy makers to review the advancement of integrating automation in agriculture in Zambia. The fact that there is limited knowledge on the effects of automation on agriculture in Zambia, it makes it very important to create a policy discourse for planning purposes to strategically prevent unemployment in the sector which mostly provides income to less skilled population. The study findings will also add to the pool of professional and academic knowledge.

1.6 Scope of the study

The study was carried out in Chisamba and Mkushi Districts of Central province. The study targeted commercial farms and included human resource managers and officers. Different kinds of automation were documented and how they affected employment in a positive and negative way.

The limitation to the study is that due to the Covid-19 Pandemic, most farmers are not open to having external visitors hence data collection for some farms had to be done virtually and some farmers did not respond to the questionnaires sent to them.

1.7 Definition of key operational terms

Automation: Farm automation also referred to as smart or digital farming/agriculture is a variety of tech innovations in traditional farming to optimize the food production process and improve quality.

Employment: Skilled or unskilled individuals earning a living by working on small scale or commercial farmers in Chisamba and Mkushi Districts.

Effect: the untended or intended loss of employment because of the introduction of automated equipment at a farm that replaced human labour. It also means the blending of human labour and equipment without loss of employment.

1.8 Structure of the chapter

Chapter one: Provided the background to the topic area and concisely stated the statement of the problem, study objectives and questions, significance of the study, scope of the study, definition of key terms of operation, structure of the dissertation and summary of the chapter.

Chapter two: Described the empirical evidence on the topic area. The chapter reviewed published articles on the topic area, and published reports. The empirical review was drawn from different regions of the world including developed countries. It was synchronised based on the theme and not on regional perspectives.

Chapter three: Provided the overarching method used to collect and report the data. The research design, approach, study population and settings, sampling, data collection, management and analysis, and ethical consideration.

Chapter four: presented the study findings. The study findings were aligned to the study objectives, and study hypotheses.

Chapter five: Under this chapter, the study findings were discussed. The discussion was cantered on the key study findings. The findings were contrasted with empirical evidence from other studies.

Chapter six: The study conclusion was provided for under this chapter by drawing from the purpose of the study, the objectives and hypothesis. The study made recommendations based on the findings and the limitations were indicated as well as the suggestion for future studies.

1.9 Conclusion

The chapter introduced the topic and background which described the main terms which mostly was the automation and agriculture-based employment. The chapter concisely explained the statement of the problem based on the background provided, the study objectives and questions, significance of the study and the scope of the study. The definition of key operation terms was also provided as well as the structure of the dissertation and the summary of the chapter. The next chapter is the literature review.

CHAPTER 2

LITERATURE REVIEW

2.0 Overview

The previous chapter introduced the topic area and provided its background by explaining facts around the key terms of the topic title. This chapter shifts the background from chapter one into a discourse by reviewing key literature on the topic area from different regions. The chapter first discusses the theoretical framework, empirical evidence based on published original research articles, published literature reviews, and reports. The chapter includes a gap analysis drawn from the reviewed literature and it ends with a summary of the chapter section.

2.1 Theoretical Framework

The section describes Human Capital Theory. It provides the origin of the theory, its definitions, and the critique from different school of thoughts and disciplines.

2.1.1 Theory of Human Capital

The study was underpinned by the theory of human capital because of its inclusive definition to contrast human capital and other forms of capital such as equipment which are of automation in nature. It also includes the blending of human and other innovation as forms of capital. The empirical evidence relates to this theory as indicated under the gap analysis section.

2.1.2 Origin of the theory

In the 1960s, economists Gary Becker and Theodore Schultz pointed out that education and training were investments that could add to productivity. As the world accumulated more and more physical capital, the opportunity cost of going to school declined. Education became an increasingly important component of the workforce. The term was also adopted by corporate finance and became part of intellectual capital, and more broadly as human capital. The possible downside of relying too heavily on human capital is that it is portable. Human capital is always owned by the employee, never the employer. Unlike structural capital equipment, a human employee can leave an organization. Most organizations take steps to support their most useful employees to prevent them from leaving for other firms (Barman and Deka, 2019).

2.1.3 Definition of Human Capital

Human capital is a loose term that refers to the educational attainment, knowledge, experience, and skills of an employee. It states that companies have an incentive to seek productive human capital and to add to the human capital of their existing employees. Put another way, human capital is the concept that recognizes labor capital is not homogeneous. Human capital the intangible economic value of a worker's experience and skills. This includes factors like education, training, intelligence, skills, health, and other things employers value such as loyalty and punctuality. The human capital theory posits that human beings can increase their productive capacity through greater education and skills training. Critics of the theory

argue that it is flawed, overly simplistic, and confounds labour with capital. Intellectual and human capital are treated as renewable sources of productivity. Organizations try to cultivate these sources, hoping for added innovation or creativity. Sometimes, a business problem requires more than just new machines or more money (Barman and Deka, 2019).

2.1.4 Critiques of the Human Capital Theory

Some economists do not agree that human capital directly raises productivity. In 1976, for instance, Harvard economist Richard Freeman argued that human capital only acted as a signal about talent and ability, real productivity came later through training, motivation, and capital equipment (Barman and Deka, 2019). Concluded that human capital should not be considered a factor of production. Around the same time, Marxian economists Samuel Bowels and Herbert Gintis argued against the human capital theory, stating that turning people input in form of labour into capital essentially squashes arguments around class conflict and efforts to empower workers' rights. In the 1980s and 1990s, with the rise of behavioural economics, new critiques were levelled at the human capital theory in that it relies on the assumption that human beings are rational actors. Therefore, the human capital theory will experience the same defects and limitations when it attempts to explain phenomena because its basic assumptions on human motives, goals, and decisions are, it turns out, not well-grounded. More modern critiques from sociologists and anthropologists argue against the human capital theory, saying it offers extremely simple principles that purport to explain everyone's wages, all the time, or, a universal connection between human capital, productivity, and income. It is argued from the social scientist point of view that for the most part, productivity differences between individuals cannot be measured objectively (Barman and Deka, 2019).

2.2 Theoretical review

2.2.1 Effects of automation on agriculture employment

Agriculture productivity and decent job possibilities may be affected by automation in a number of ways. It becomes possible to increase the amount of farmed land or the yield per hectare in crop production, both of which lead to an increase in output. By allowing workers to milk or feed animals with little to no physical assistance, automation can increase labour productivity and significantly reduce drudgery in the production of livestock (FAO, 2022).

Forestry, aquaculture, and fisheries all follow a similar line of thinking. Improved worker safety is a significant additional benefit pushing automation in the forestry industry. The welfare rate may significantly rise as a result of all these benefits. If automation includes significant economies of scale, broad adoption among larger manufacturers may occasionally drive out smaller producers and lead to industry consolidation. Automation can displace people, especially the poorest ones who may struggle to find work elsewhere when the demand for agricultural labour declines and new technology renders some skill sets obsolete. In order to avoid, reduce, or alleviate the negative societal repercussions, particularly for the most disadvantaged, appropriate policies, legislation, and investments must be made (FAO, 2022).

The effects of agricultural automation on employment are challenging to assess because they frequently involve adjustments to various agricultural production activities, as well as upstream adjustments resulting

from shifting input demand and downstream adjustments affecting transport and logistics, processing, distribution, and retail. Many leave agriculture as it undergoes transformation in search of better-paying occupations, and the proportion of people working in agriculture is falling. As it affects the production, processing, and distribution of food and other agricultural products, the process reshapes labour supply and demand in all agri-food systems (UNCTAD (United Nations Conference on Trade and Gender, 2020).

It is challenging, if not impossible, to link specific instances of agricultural automation to social repercussions like changes in decent employment and the implications for gender, youth, and small-scale producers when all the nodes in agri-food systems are changing more or less concurrently. Understanding the changes to agri-food systems is essential to understanding their social effects, particularly on employment. It does not take into account the potential consequences on the entire economy, which could have important social repercussions as well as the potential indirect effects of automation adoption (such as the rise in need for researchers and scientists to create and enhance technologies). The individual circumstances in various nations and communities will determine how the whole range of potential final repercussions manifests itself in practise (FAO, 2022).

First, there are several potential implications of agricultural automation, all of which could have a variety of repercussions on farm employment. When more jobs are mechanised, there will likely be less demand for low-skilled labour, whether provided by family members or paid help. Worker bottleneck issues may be solved by automation of some jobs, allowing production to rise through horizontal expansion or intensification. Automation is projected to increase the need for individuals with average skill levels to support emerging technology (ILO (International Labour Organization), 2022).

Second, compared to the effects on specific agricultural company sites, the general effects of agricultural automation on decent employment throughout agrifood systems are likely to be considerably different. Automation might readily increase higher-paying, less seasonal work upstream and downstream while decreasing low-paying seasonal jobs on farms. It is unclear if the rise in higher-paying, less seasonal labour will be enough to offset the negative effects of the decline in employees' access to low-paying seasonal job, allowing those individuals to choose alternative employment (FAO, 2022).

Seasonality in employment is a problem in agriculture all around the world. Production activities for crops and cattle are inevitably seasonal. This means that while there may be acute labour shortages in some seasons, unemployment and underemployment tend to be high in others. Lack of labour at crucial times for an agricultural producer (such as during crop harvest and livestock shearing) can have major effects on farm operations and may result in losses or discourage farming entirely(FAO and AUC, 2018).

Theoretically, employment might be maintained in other seasons if automation reduces the excess labour demands during particular seasons. This prompts significant queries. Which farming activities are the simplest to automate, and do they correspond with the labour shortages farmers experience during particular seasons? What, on the other hand, will happen to the lowest paid, least qualified individuals when enterprises begin to automate and their skills become obsolete? Which laws can guarantee an automated process that is more productive, effective, sustainable, and inclusive?

Tasks occurring in labour-scarce seasons are frequently the most difficult to automate for the most labour-intensive crops, especially fruits and vegetables, due to the risk of machine damage to plants or fruits. Consider automation in the wealthiest agricultural regions, where farm salaries are generally high and

automation solutions are most accessible, as an illustration. In California, United States of America, land preparation activities like tilling, ploughing, and levelling the ground are all completely automated. Automated harvesting is used for crops that will be processed, such tomatoes and wine grapes (FAO, 2022).

Although produce-picking robotics solutions are in the works and are being encouraged by a shortage of harvest workers and quickly rising salaries, the harvesting of fresh fruits and vegetables for final consumption still relies on manual labour and is more difficult to automate. Numerous different types of workers are suitable for these new job prospects. Although though they all need only a minimal amount of formal schooling, drivers, warehouse employees, machine operators, and mechanics have different pay scales, job security, and skill requirements (Ogwuike et al., 2014;Castro et al., 2015).

These positions may also be seasonal, particularly in small processing businesses, but if they are provided by large commercial processing companies, they may be steady. They are less seasonal in both instances than agricultural field work. Men fill the great majority of positions (Hansen and Stræte, 2020;Taylor and Charlton, 2018). The best paid jobs are for office workers, salespeople, and specialists who need more formal education, training, and experience. These jobs also often have a higher percentage of female employees (Daum and Kirui, 2021).

2.2.2 Effects on small-scale and subsistence farmers

Production and the nature of job have an effect on labour demand. Family labour is used by subsistence producers to run their production facilities. They frequently lack access to markets and services, are food insecure, and are poor (Maucorps et al., 2019; Charlton et al., 2019). Up to 83 percent of small-scale producers in the Plurinational State of Bolivia live in poverty, which is higher than the 61 percent national average. The poverty headcount ratio for small-scale producers in Ethiopia, where 30% of the population falls below the national poverty line, is 48%.

More than half of Vietnam's small-scale producers are poor, compared to the nation's overall poverty rate of only roughly 20%. Given these circumstances, the higher rate of poverty among those who work in agriculture is at least partially a result of their poor productivity levels because they rely on subsistence or near-subsistence farming to survive. These farms might potentially transition into family commercial farms if they adopted automation because it would increase productivity, improve incomes and livelihoods, and increase production. For instance, Zambia's small-scale family farms that had access to tractors were able to increase their yields by 25% and more than double their incomes by cultivating more land and using more inputs, notably fertiliser.

Implementing automation can result in time being freed up for other tasks, such children's education, and have a positive long-term economic effect on households. Where jobs are available, it can also help members of the household obtain employment outside of farming. If rural households' produce is of constant quality and quantity, agricultural automation can also provide access to higher-value markets and allow them to sign contracts with supermarkets or overseas purchasers. Agriculture-related households can benefit significantly from participation in such high-value markets.

Small-scale vegetable growers in Kenya who entered into contracts with supermarkets saw a rise in household income of more than 40% as well as the highest decreases in multidimensional indicators of

poverty for the poorest households (Charlton et al., 2019). Also, farm households that supply shops with items have shown much higher calorie, vitamin A, iron, and zinc consumption (Ali, Nagalingam and Gurd, 2017).

There is evidence that a lack of agricultural labour restricts production, even in other parts of Africa where labour is relatively plentiful and fertility rates are high. Automation thus provides the opportunity to raise household income and productivity. The current efforts to mechanise agriculture in Africa are justified, according to an analysis of farm-level data from four nations in Eastern and Southern Africa, as labour and other sources of farm power seem to be significant factors restricting agricultural output in the region (Bourlakis et al., 2014).

Numerous potential advantages of agricultural automation are neither automatic nor immediate. Subsistence farmers and small-scale farmers are unable to take advantage of agricultural automation's prospects due to a lack of managerial and technical capabilities. In order to comply with the standards and requirements of the current market, they must also modernise and update their business models. This emphasises how critical it is to have rural advisory systems that are efficient and capable of ensuring timely access to information about markets and technologies. Commercial family production facilities are run and owned by family members, while they may also use paid help (e.g. hired field workers, labour supervisors, and contractors).

All three types of labour can be less in demand due to automation, but it can also encourage manufacturers to increase their production. Family labour will probably be replaced by hired professionals, such as farm managers, sales staff, machine operators, and mechanics, if family commercial producers decide to go towards corporate commercial agriculture. Agricultural automation will tend to raise labour productivity and earnings if, as is frequently the case, growing wages and a lack of labour drive technology adoption. In this scenario, automation might improve welfare for both producers and hired employees.

Automation, however, can also displace people, particularly the poorest and least talented ones, who will be compelled to seek employment elsewhere, potentially pushing wages for unskilled labour down as their skill set makes it challenging for them to find other positions. Another potential is that commercial farms' use of technology would force subsistence farmers to completely give up farming, a phenomenon known as "farm consolidation". It's important to note that this is a placeholder page and will not be updated. During the transition, it can be required to offer specialised social protection and training.

On corporate commercial farms, all forms of labour are employed with the exception of family labour. These farms are the most advanced and frequently have a high level of automation. Companies frequently have the economies of scale and financial resources to invest in cutting-edge robotics technology, which could significantly reduce the need for on-farm labour and potentially have a negative effect on workers, particularly low-skilled workers, or change the type of labour needed on farms. A former tractor driver may, for example, use digital automation to manage a fleet of autonomous agricultural vehicles or undergo maintenance training.

Robots are often not economically feasible for most farms, unless labour is in short supply. For instance, even though robotic milking technology has been used commercially for many years, few American dairies have adopted it since farm labour is still relatively affordable (Agricultural et al., 2020). On the other hand, Western Europe has been using them commercially since the 1990s.

The practice of burning sugar cane prior to harvest has been outlawed in Brazil starting in 2020 for environmental reasons, according to a set of laws and regulations. As a result, automated harvesting became more and more popular among sugar cane producers, ending the tradition of manual harvesting, which entails burning sugar cane before it is harvested. The workforce directly employed in the production of sugar cane was predicted to decrease by 52–64 percent as a result of this legislation, despite the fact that it has improved the environment through reduced pollution and higher productivity.

While the demand for skilled labour in the industry was anticipated to rise, the least qualified workers (those with no more than three years of schooling) would be the most adversely effected. To safeguard the most vulnerable from the negative consequences of automation, such shifts in the employment landscape require rapid public response.

In general, there is a risk of job loss and worker displacement if automation technologies are deployed in areas where there is no labour shortage but they are artificially made affordable (for example, by government subsidies). Farm employees may incur costs as a result of labour displacement; the overall effect will depend on whether they can relocate to new occupations created upstream or downstream. The introduction of agricultural technology, on the other hand, is likely to boost wages and total productivity, benefiting both farmers and hired labourers, as a result of higher wages and increased competition for scarce labour.

Automation on farms in high-income nations or regions within nations may adversely affect migrant remittances to less developed nations and regions. Reduced demand for unskilled migrant agricultural labourers could lead to higher unemployment rates in the host countries and areas of migrants and a decrease in remittances (Ali and Aboelmaged, 2021). Automation of the coffee harvesting process in Brazil has greatly decreased the demand for unskilled labour, which is primarily internal migrants from the country's poorer regions, but boosted the demand for trained personnel (Daum, 2021). This demands for quick-acting, all-encompassing social programmes to assist unskilled workers who lose their jobs in finding new ones.

Automation appears to frequently take place in conjunction with declining farm labour and rising salaries in migrant-sending regions. A developing labour shortage in the towns in Mexico that send out migrant workers is what is driving agricultural automation in the United States of America. Another study conducted in the United States of America discovered that the automation of greenhouses enhanced horticulture enterprises' gross revenue, enabling them to pay migrant employees higher wages and keep them on the job longer while reducing the number of new skilled hires they made (Streed et al., 2021).

Countries look to immigration as a fresh source of farm labour as crop productivity rises and the availability of indigenous farm labour declines. For instance, in California, United States of America, immigrants make up more than 90% of the farm labour force. Nowadays, high-income nations are almost universally dependent on immigrant farm labourers. It could appear that automation would have a detrimental effect on communities that send migrants. Agriculture in California is automated, but this is not a standalone phenomenon.

The majority of immigrants live in Mexico, where fertility rates are declining, school enrolment is substantially rising, and there is greater access to non-farm jobs, which reduces the availability of workers in rural areas. Construction of secondary schools in rural Mexico is bringing education to boys and girls

who might otherwise seek employment in agriculture, hastening the change of agriculture. In fact, even when they depart, those with higher education are more likely to work in non-farm industries(Schillings, Bennett and Rose, 2021) As a result, California's agricultural labour pool has drastically decreased, which has led to an 18% quicker growth in agricultural wages between 2008 and 2018 than in non-agricultural wages.

In California, there was little motivation to adopt and develop innovative labour-saving technology prior to the fall in the availability of farm labour in Mexico in the 1990s. Automation and a dwindling farm workforce are currently competing in both countries. The most labour-intensive and straightforward operations are typically the first to be automated, but as more sophisticated solutions are created and made available for purchase, countries like the United States of America are beginning to automate more difficult tasks like picking fruits and vegetables.

2.2.3 Effects on women

The effects of on-farm automation on gender are complex and wide-ranging. They rely on the prior gender distribution in carrying out newly automated manual agricultural jobs as well as on the gender labour distribution in agri-food systems and homes (e.g. distribution of assets). On farms, there are frequently fairly strict gender distinctions. For instance, in Morocco, the crocus flower, from which saffron is extracted, is grown primarily by males, but processing the blooms, which requires arduous, labour-intensive work, is nearly entirely done by women (UNCTAD (United Nations Conference on Trade and Gender, 2020). As a result, automation in the flower industry would free up mainly male labour. Also, if it boosted flower production, there would be a greater need for female labour. This may be good news for employed women, but it's horrible for women who work for families.

Men and women in Zambia shared labour-intensive duties in a case study (e.g. weeding). The adoption of tractor services for land preparation led to an increase in cultivation, although this did not disproportionately burden women or children. Instead, everyone in the family was able to spend more time relaxing (National Farmers' Union, 2019). Further evidence from Eastern and Southern Africa demonstrates that, in many cases, the machinery of land preparation replaces labour performed by both men and women, but mainly women, who are primarily in charge of weeding, which is labour-intensive work (Bourlakis et al., 2014).

The advent of motorised mechanisation in Western Kenya also gave both men and women more time, allowing the household to boost spending on children's education (FAO, 2019). These instances highlight the need to take into account specific gender roles when considering how automation would affect women. It is crucial to avoid making ill-informed generalisations about how automation will mostly benefit men because it will automate their tasks. Seek out additional instances of women and young people using agricultural automation technologies successfully.

Research suggests that women lag behind men in adopting agricultural technology due to barriers in access to capital, inputs and services including information, extension, credit, and fertiliser are limited physical accessibility, and cultural norms. This is despite the potential of on-farm automation to ease women's time and work burdens while enhancing productivity, income, and welfare (Autor, 2015). In the coastal zone, for instance, 78.6% of female farmers, according to the Ghana Institute of Management and Public Administration, cannot get tractor services (ILO (International Labour Organization), 2022) Due to

lower literacy rates, a lack of appropriate tools and equipment, a lack of infrastructure, and inadequate funding for women's extension programmes, women are frequently unable to adopt automation technology and cannot accept occupations that demand expertise in farm operation and management (ILO (International Labour Organization), 2022).

At the farm level, males typically handle business transactions involving agricultural automation services. As a result, males control the resources needed to invest in automation (particularly capital) and make the decisions (ILO (International Labour Organization), 2022). Agricultural tools and equipment are typically made to fit men's ergonomic requirements, with little thought given to women's needs (Christiaensen, Rutledge and Taylor, 2021). Due of their mechanical complexity, physical demands, and challenges in hiring and supervising labourers, women in Bangladesh do not use irrigation pumps (Daum and Birner, 2020). Gender-friendly automation technology must be developed and made available.

In fact, a recent literature review emphasises the necessity to take gender variations into account in future research and policy in order to lessen the stress of work on women and improve welfare results (Autor, 2015). In order to improve productivity, safety, comfort, and eliminate drudgery as part of an overall sustainable development of society, these gender-based limitations must be removed (Christiaensen, Rutledge and Taylor, 2021). Policymakers and local implementation partners should evaluate the enabling environment and support gender-sensitive technology development, dissemination, and service provision in order to encourage women to embrace technologies. Technologies that are gender-sensitive take into account both male and female physical traits (FAO and AUC, 2018).

Women's competence and autonomy should also be supported, as well as gender equality in the ownership and/or control of important productive assets (Clarke, 2017). Positive results can emerge from targeted tactics and initiatives that simultaneously address the barriers to technology adoption that women experience at the household, service, and policy level. Research from Ghana, for instance, indicates that training women in nodes of the value chain that are normally controlled by men can benefit not only women but also the larger community (ILO (International Labour Organization), 2022).

By breaking down barriers for women in agricultural automation, traditionally a male-dominated field, the Women in the Driving Seat tractor training programme strives to advance gender equality. The goal of the training project is to actively promote women's leadership and participation in using agricultural machinery in Ghana. 182 female tractor operators have been certified as a result of the programme since 2018. Women can excel at operating and maintaining tractors, as seen by the completion rate. The Women in Tractor Operating Association was founded by graduates as a means of organisation and mutual assistance.

Women's participation in automation has changed the thinking of not only other women but also professionals, employers, and the general public. These newly working women now play an important role in the maintenance of a secure home environment and decide how to allocate resources and money. Hence, the initiative has fostered gender equality at work and at home (ILO (International Labour Organization), 2022).

The possibility of hiring services is further highlighted by an analysis of the disparities between men and women's participation in Bangladesh's burgeoning marketplaces for reaper harvester machinery services (Daum, 2021). Women specifically profited from operating and occasionally owning machinery businesses

as well as from the direct and indirect effects of using such businesses to harvest their crops. Efforts to promote hire services ought to put an emphasis on involving women, both as company owners and as users of machinery.

2.2.4 Effects on youths

The first to embrace agricultural innovation seems to be young farmers. They are consequently seen as being important in agricultural transformation and generational change (Gaus and Hoxtel, 2020). Agricultural automation promises new employment categories that are distinct from the sector's traditional jobs, which are frequently connected to subpar, riskier, and underpaid working conditions. These new employment involve cutting-edge technologies that call for specialised abilities to effectively use them, resulting in fair pay and safer working conditions.

According to a recent report on stakeholder attitudes on mega-topics for the reform of the African agricultural sector, 78–98% of stakeholders feel that farming can attract young people. Nonetheless, a sizable portion of respondents (between 72 and 97 percent) felt that young people are not properly active in policymaking, and a sizable portion claimed that young people lack role models in agriculture (48–79 percent).

Also, there is a belief that school systems, particularly in Benin (70%) and Kenya (63%) do not effectively equip young people for the job market (Fielke et al., 2018). Most rural youngsters (McCampbell, 2022), who are unable to obtain highly specialised professions, must thus develop the relevant abilities. Government policies and investments should place a high priority on a robust human capital development and capacity-building agenda, with an emphasis on youth (Gaus and Hoxtel, 2020).

2.3 Empirical Evidence

The section presents the thematic areas of the literature review aligned to the study objective:

2.3.1 Kinds of automation used in agriculture sector

There are manifold of automation on the agriculture market, conventionally tractors are the main focus of point of entry for automation in developing countries (Adu-Baffour and Birner, 2019; Daun and Heni, 2020). Sectors such as aquaculture still use traditional methods (Maulu, 2019). However, automation in agriculture has advanced to a level of incorporating digitised devices. There are now robots that are codifiable (Millington, 2017) to drive tractors without a driver and to pick fruits and vegetables, and drones to monitor crops, detect specific soil and irrigation needs, ripeness of fruits and vegetables and health of animals (Gaus and Hoxtel, 2020).

The Gaus and Hoxtel, (2020) study questions whether automation is a major threat to Sub Saharan Africa (SSA) workers. For the most part, the answer is no. At least not yet. The SSA countries, or significant parts of their economies, lack the infrastructure and capital for even a limited use of the automation technology. Many countries on the continent are yet to implement earlier technological breakthroughs, including mechanization and digitalisation, on a larger scale. This effectively hinders most SSA countries from the introduction of advanced automation technologies. Moreover, their informal economies consist largely of subsistence farmers, street vendors, and day labourers, and abundance of labour and, consequently, low

pay make it cheaper to have human workers instead of robots or software doing the job. These findings indicate that SSA countries are in a dilemma because of what the emerged polarisation between automation and intensive labour. The discourse of preferring the means of one form of production over the other is dependent over which one is cost effective and efficient. This poses a big human resource dilemma, except that the extent of automation in the agriculture sector in Zambia is not yet well understood or measured.

Agriculture is broad, and technology or automation may have advantages depending on what the use is for. When it threatens employment it rises debate about job security, and when it is used for mass production to meet demand it is highly considered. Another review study by Maulu (2019) was concern about the technology used in aquaculture in Zambia. The review indicated that the country's aquaculture industry is still lagging behind in some critical areas as the majority of producers are still using traditional technologies which have made it difficult for them to make significant contributions to fish production. As a result of this lag and other reasons, the country has witnessed an unprecedented importation of fish to meet the deficit and the ever-increasing demand. Therefore, efforts to accelerate and sustain aquaculture industrial development in Zambia must address such areas of science and technology as fish genetic breeding and improvements, fish health and disease management, sustainable feeds and nutrition, production systems, and water environmental management.

2.3.2 Skills affected by automation in agriculture sector

Millington (2017) study asserts that those that are highly trained and skilled are more likely to lose jobs to automation than the less skilled ones. The study further observed that developing countries are more at risk than developed countries because that is where intensive labour is widely practiced. Millington (2017) study simply agrees with Lima et al. (2021) study findings except that the two studies had limited insight on how automation would affect employment in the agriculture sector. Also, the studies underestimate the effect of automation in unskilled unemployment sector which is largely agriculture. Because vulnerability to automation is now based on whether jobs or tasks are codifiable and whether they are routine or not (Millington, 2017).

2.3.3 Effect that automation has brought on employment

A study titled "The effect of automation of agriculture on the digital economy" was carried out by Guzueva et al. (2020). The study examined the development and effect of digital technology on various sectors of the digital economy in Russia with a huge focus on agriculture. The study recognised the importance of automation culture in present day agricultural activities. It provides a huge positive effect on the national economy of all countries implying its necessity. Innovation considers improved harvest creation by understanding soil wellbeing. It enables ranchers to utilize fewer pesticides on their yields. Soil and climate observing diminishes water squander. Advanced horticulture in a perfect world prompts financial development by enabling ranchers to get the most generation out of their territory. Ultimately, it helps economic growth pompously. However, the study also established forms of vulnerability among the low-skilled migrant labour community that are being replaced by automation technologies. This study rightly shows the effect of automation on agriculture employment, the study having been done in Russia, in a developed country, the effects of automation are not known in a developing country like Zambia.

On the other hand, in Australia and New Zealand, a report by Murphy, (2020) titled “Robots won't replace workers in labour-intensive agriculture sector: CSIRO” argued that despite the automated agriculture filling up the shortage in the agriculture sector it will not replace human intensive labour. Farming like horticulture and shearing still require labour intensive workforce. The report started that automation would continue to be blended with human-intensive workforce, as experienced by the Toyota Automobile which had replaced human power completely but later realised that the automation required human manpower workforce.

The findings of Murphy, (2020) are supported by the revelation of Liu, (2020) in a report titled “Will Agricultural Robots Replace Human Agricultural Labour? | Opinion”. The reported revealed that it should be ensured that robots and automated devices do not evolve to disrupt workers but to aid them and improve their working conditions. In fact, robots and automation might even help workers earn a higher salary, as many primary workers earn bonuses depending on volumes of harvest and how fast they can deliver their products. With most primary workers earning minimum wage, and illegal workers earning much less than that, robots and automation might help them to meet their bonus objectives without exposing themselves to unendurable physical pressure.

Gaus and Hoxtel, (2020) conducted a study titled “Automation and the Future of Work in sub-Saharan Africa (SSA)”. The study confirmed that numerous technological advancements in the agricultural sector have increased productivity while decreasing the need for human labour, including driverless and autonomous tractors, fruit and vegetable picking systems, and drones for monitoring crops. However, most disruptive for the agricultural sector is the combination of self-learning autonomous robots doing manual work such as harvesting crops with sensors and pattern recognition that can detect soil specifics and irrigation needs, weeds, ripeness of fruits and vegetables, or animal health.

In South Africa, the Landmark Underwriting Agency (Pty), (2020) report states that the risks facing South African farmers such as weather-related incidents, rising input costs and the threat of violent crimes are likely to lead to increased automation in the local agricultural industry. This is rather interesting because literature consistently indicate that labour-intensive costs push investors in agriculture adopting automation-intensive, however, in South Africa it is a combination of factors. At the same time the report stated that the other reason for possible transition to automated agriculture will be the demand for increased minimum farming wages combined with energy hikes in electricity and fuel.

Another study by Adu-Baffour, Daum and Birner, (2019) study in Zambia analysed an initiative by John Deere a farming technology firm with global presence. The study revealed that mechanization causes rural unemployment despite the double in income because of increase size of cultivated land. It also reduced child labour and increased hired labour. The focus of the study was creation of demand for the mechanised agriculture unlike preservation of employment in agriculture at household levels. The study was titled “Can small farms benefit from big companies’ initiatives to promote mechanization in Africa? A case study from Zambia.”

Similar findings were reported by Daum and Heni, (2020) in a study titled “What are the effects of agricultural mechanization? A case study from Zambia”. It stated that mechanisation is a concern that could lead to unemployment. This study suggests, that in situations where an expansion of the cultivated area is feasible, mechanization even increases the demand for hired labour. This effect was amplified because the increased income achieved by mechanization allowed farmers to replace family labour.

2.3.4 Measures of reducing effects of unemployment in the agriculture sector due to automation

A generic study on automation titled "Understanding Technological Unemployment: A Review of Causes, Consequences, and Solutions" was carried out by Lima et al., (2021). The study was a literature review, and although the focus of the study was broad looking at the effect of automation, it indicated that technological unemployment is a reality. This study did not focus on agriculture, however, agriculture being the largest source of income around the world especially in low- and middle-income countries millions of people are likely to be unemployed when the transition to automation is scaled-up. The study suggests that technological unemployment can be curbed by tax reforms, negotiation for minimum income guarantees, reducing working week, and reforming higher education. What these solution entails is that human skills have become more expensive, and automation is the cost-effective measure, as an alternative labour input.

In Zambia, Mukhalipi, (2018) conducted a study titled "Human Capital Management and Future of Work; Job Creation and Unemployment: A Literature Review". The review indicated that the future of technology advancement, automation in the agriculture sector might disrupt economic and social activities in developing countries including Zambia by the year 2026. The review recommended that development strategies on human capital development should address the challenges associated with low labour productivity and how technological advancements, automation in the service sector will sustain jobs that Zambian Government will have created for the locals by the year 2026. It further stated that development strategies on human capital development which will ensure that most workers which enter the labour force after dropping out of school, attain basic numeracy, Information, communication and Technology and literacy skills by 2026. These study findings were based on secondary data, literature review. The review comprised literature from different developing countries, whereas this study was based on primary data.

2.4 Gap Analysis

The human capital is centred around development of human skills as an input for production of farm commodities, and according to the moot points from the reviewed empirical evidence the human capital is threatened by robotic and automation invention on one hand. On the other hand, the threats of robotics and automation can be thwarted because human capital is more dynamic and automation will still depend on it. These arguments are relative to context in which the study was conducted in and limited to the type of automation or mechanisation looked at. In Zambia, it was the assessment of John Deere Tractors and its effect on intensive labour. However, automation is not limited to tractors, there a number of automation used in agriculture that this study looked at. In other context drones are used, monitoring of moisture in the soil, harvesting and other digitised inventions are used. In Zambia, the extent of the effect of such automation on employment are not unknown to advance practical solution to the growing threat of unemployment due to automation. The empirical evidence reviewed in Zambia was mainly based on literature review, except for Adu-Baffour, Daum and Birner, (2019) and Daum and Heni, (2020) which focused on John Deere tractors. The evidence which was closer by , Mukhalipi, (2018) was a literature review and it comprised of articles across the region. Therefore, primary data was required to provide evidence on the topic area.

2.5 Summary

The chapter provided the literature review which was underpinned by the human capital theory in theoretical and literal terms. The empirical evidence was drawn from published articles and reports from different regions, and locally. Further, the chapter provided the gap analysis drawn from the empirical evidence. The next chapter is the research methodology.

CHAPTER 3

RESEARCH METHODOLOGY

3.0 Overview

Chapter two presented evidence on automation and agriculture employment. The reviewed evidence showed that most studies used Survey designs, and this chapter presents the study design used under research methodology. The chapter consist of the research philosophy, design, approach, study population and sampling, data collection method, management, analyses, validation and reliability, ethical consideration. The chapter ends with a summary.

3.1 Research Philosophy

There are number of paradigms that constitute research philosophy. Among them is the Positivism, Interpretivism and the pragmatic paradigm (Creswell, 2014b). The positivism paradigm is based on objectivity methods of data collection in a study. That is a study group or population is observed as an object independent of interference from the researcher whereas the Interpretivism is an emphatic paradigm where data is collected as narrative by a study individuals or group. The researcher emphatically involved in data collection because the researcher's observation adds to the data analysis. The Positivism methods can be applied at a population level as opposed to the Interpretivism. When the two paradigms are combined a pragmatic paradigm is formed. Usually, the paradigm is used for practical oriented studies such as operational studies to observe the implementation of an intervention of activities. It is practical in nature; hence the study used the pragmatic paradigm. Pragmatic paradigm applies research design that accommodates both the positivism and Interpretivism (Saunders and Tosey, 2013).

3.2 Study design

The study design both Cross Sectional and Phenomenology. The Cross Section was for the quantitative component while the phenomenology for the qualitative one. However, both designs were applied concurrently.

3.3 Quantitative design

It was a Cross-Sectional study design of Chisamba and Mkushi farms. A Cross-Sectional design was used because it allowed data to be collected across different places/farms in a short period of time. It was also appropriate to allow for the capture of current use of automation in agriculture, which makes it cost-effective because little time is spent on data collection (Saunders and Tosey, 2013). Population level data was collected that would enable make inferences based the hypothesis. The use of longitudinal, cohort or case study design would have taken a long time and costly. Longitudinal and cohort studies require a periodical interval of follows of about between three to six months in between for a year or more. Case study design also require enough time to observe and interrogate cases. The Cross-Sectional design was a better option for paving way for much finer analysis design such as longitudinal, cohort and case study designs.

3.4 Qualitative design

Qualitative design was applied to all the quantitative cases, the study design used was the Phenomenology (Saunders and Tosey, 2013). The design was suitable to capture real life experiences of human resource officers on automation in agriculture and affected people. These were experiences as lived and constructed by the human resource managers hence they interpreted them from their social reality.

3.5 Study approach

A descriptive mixed approach was used. This consisted of quantitative and qualitative data collection methods. The two approaches were conducted concurrently, and the reason for using the mixed method was for triangulation (Creswell, 2014a). Because population level data collection included the human resources managers; the human resources experiences complemented the quantitative data to explain the hypotheses and the frequencies and percentages.

3.6 Study Population and Sampling

There are 400 farmers in in Zambia (Tembo, 2020). Therefore, the study used Taro Yamane formula to calculate the number of farms that were included the sample size.

$$\mathbf{n} = \frac{\mathbf{N}}{\mathbf{1} + \mathbf{N}(\mathbf{e})^{\mathbf{2}}}$$

The formula denotes that; 'n' is the sample size to be determined. While the capital' N' is the target population, and 'e' is the margin of error at 0.05 (5%) with a confidence level of 95% (0.95 proportion.

$$\mathbf{n} = \frac{\mathbf{400}}{\mathbf{1} + \mathbf{400}(\mathbf{0.05})^{\mathbf{2}}}$$

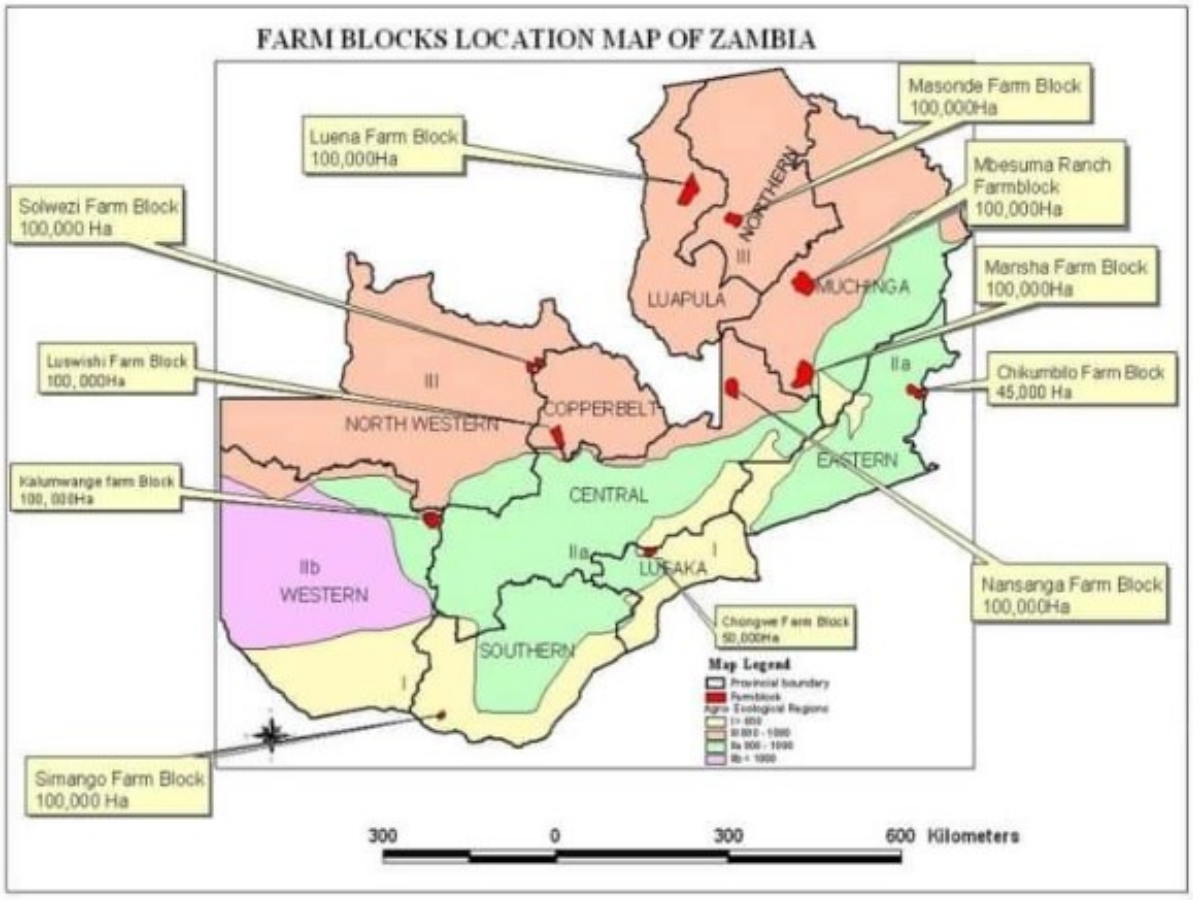


FIGURE 2: FARMING BLOCKS IN ZAMBIA

The sample size was 200 commercial farmers. Since the number of farmers for each district were not known, the 200 number of commercial farmers was distributed across the two districts of Mkushi and Chisamba. There were 100 commercial farmers selected in each district.

3.7 Sampling Technique

The study used a non-probability sampling technique to select the commercial farmers that took part in the study. Convenient sampling was used, and purposive sampling was applied to select the study respondents at each farm.

3.8 Data Collection method

Interviews were used to collect data. The interviews were administered by a research assistant. The interviewees who were human resource managers and officers were visited at their farms, and interviews appointment were arranged on the spot. For farms that are not welcoming people to their farms due to Covid restrictions, phone calls were made to them, and short messages were sent, and virtual appointments were arranged.

3.9 Data collection tool

The study used a Semi-Structured Interview guide. The interview guide had four sections consisting of background information of the study respondents, kinds of automation used, the levels of skills affected by automation, and kind of commercial farms sing automation. There was an open-ended question for each closed ended question for in-depth interviews.

3.10 Data management

After each interview the data was checked for thorough entries and errors were corrected before the research assistant left the farm. The data was transferred from the word document to Excel spread sheet and the qualitative data was transcribed on to word document using Microsoft Office Word and Excel. The quantitative data was pre-coded, only the codes were entered on the Excel Spreadsheet while the qualitative data was transcribed into common questions form the interview guide.

3.11 Internal data validity and reliability

3.11.1 Quantitative

The closed-ended questions were standardised. These were pre-tested before the actual data collection to check for consistency and precision. The pre-test study was conducted among smallholder farmers in Lusaka West, 30 of them took part. Some questions were revised to improve them measure data with consistency and precision.

3.11.2 Qualitative

Member-checking was used to verify interviewees' responses. A trail of data was observed to and reflected on to pattern for further follow up with subsequent participants. Duration of involvement with the study participant was short to reduce on subjectivity or empathy, the research assistant debriefed with the principal investigate on a daily basis, and negative case analysis was used to gain a deep understanding of the rare cases.

3.12 Data analysis

3.12.1 Quantitative

The Excel spreadsheet was exported onto Software for Social Science Package version 14 of IBM. The data was further cleaned to ensure the observations were consistent. The study analysis involved the summarising of each section in the interview guide by using frequencies and percentages. The Chi square statistical test was used as measure of association between the use of automation in agriculture and unemployment. This provided the response to the hypothesis. The 0.05 threshold for statistical significance was used to determine the association or the rejection or fail to reject the null hypothesis.

3.12.2 Qualitative

Thematic framework was used to analyse quantitative data. Transcribed data read through, and single meaning of text were written up under each question. The questions formed the themes. The single textual meanings with similar meaning were combined and summaries written up. Quotations were identified and align to the summaries.

3.12.3 Integration of data

Quantitative and qualitative data were combined chapter four by presenting data side by side. The side by side presentation of data was meant at ensuring that each objective was complemented by the two study approaches. The difference in the two datasets were also presented and discussed in chapter five.

3.13 Ethical consideration

Permission to conduct the research was sought from the University of Zambia School of Humanities and Social Science Ethics Committee. Authority to collect data was requested from the commercial farm owners. Full study information was provided to the human resource managers/officers. The study respondents were assured of confidentiality and autonomy participation in the study. There was no compensation for the time and energy used taking part in the study and the respondents were explained to. Their participation was based on goodwill. They were told that they had the right to continue and withdraw their participant at any time their wished. There was no personal or farm identifier details were collected to preserve the anonymity of respondents and the farms.

3.14 Summary

The chapter presented the research philosophy the underpinned the study data collection. It further explained in detail the study design and approach as guided by the research philosophy. The study used the population of commercial farmers in Zambia to calculate the sample size. The data analysis was conducted separately, and the data was integrated under the study findings chapter. Ethical consideration that guided the social contract between the study and respondents was explained. The next chapter is the presentation of the study findings.

CHAPTER 4

PRESENTATION OF STUDY FINDINGS

4.0 Overview

The previous chapter demonstrated how the data was generated. This chapter presents the data that was generated in an analysed way for easier comprehension. The findings are presented according to the study objective themes which consisted of; kinds of automation used, Individual skills affected by automation, and kind of commercial farms use automation themes. The chapter first presents the respondents' characteristics before the key findings.

4.1 Respondents' Characteristics

The characteristics of study respondents are presented in table 1 and figure 1 to .3. These consisted of the mean age, gender, levels of academic qualifications, and proportions of respondents' form each of the two districts. The brief description of the findings is presented at the end of this section, and only outstanding proportions or absolute numbers are described.

There were 138 respondents, and their mean age was 49 years old. The age range was from 25 to 68 years old with a standard deviation of 14 years. Of these 88 % (122/138) were males, those with Bachelor of Arts or Science degrees were 41% (57/138), and 70% (97/138) of the respondents were from Chisamba District and 30% from Mkushi.

4.1.1 Age

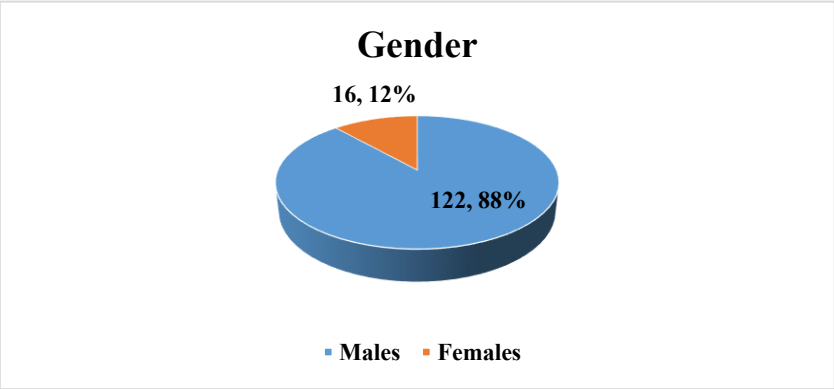
Table 1: Mean Age of Respondents

Age in Years	Number of Respondents	Minimum	Maximum	Mean	Standard Deviation
	138	25	68	49	14

Source: Author (2022)

4.1.2 Gender

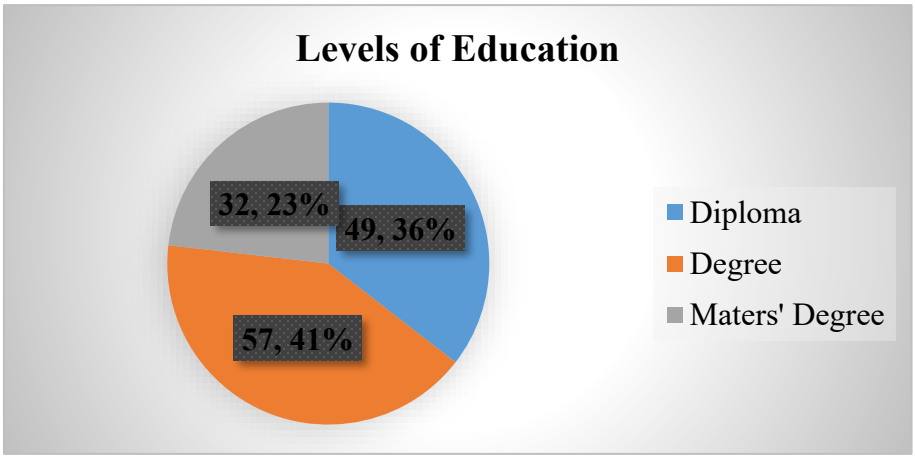
FIGURE 3: GENDER OF RESPONDENTS



Source: Author (2022)

4.1.3 Levels of Education

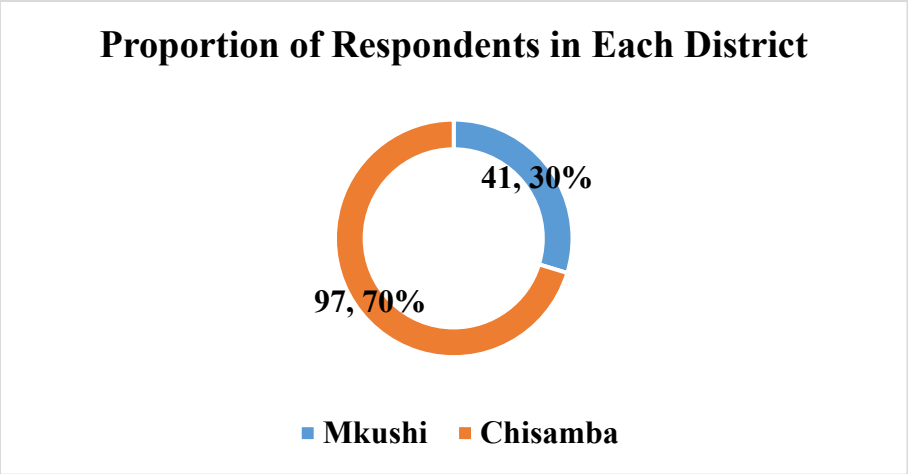
FIGURE 4: RESPONDENTS' LEVELS OF ACADEMIC QUALIFICATIONS



Source: Author (2022)

4.1.4 Proportion of Respondents in Each District

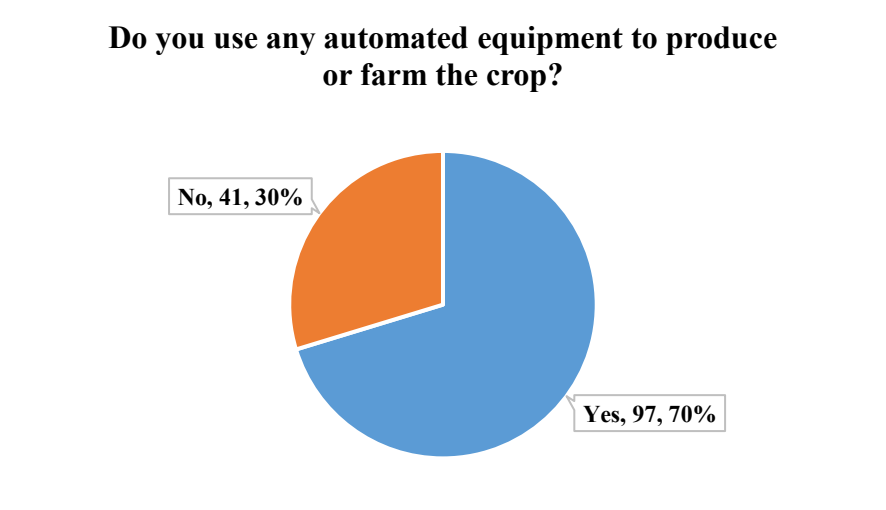
FIGURE 5: PROPORTION OF RESPONDENTS PER DISTRICT



Source: Author (2022)

4.1.5 Kinds of automation used

FIGURE 6: PROPORTION OF AUTOMATED FRAMING



Source: Author (2022)

Of the 138 commercial farmers, 70% (97) reported using automated equipment to farm (figure 4.2). Commercial farmers used different kinds of automated equipment for farming activities. The equipment they used ranged from heavy duty equipment to light duty devices. The said that heavy duty equipment

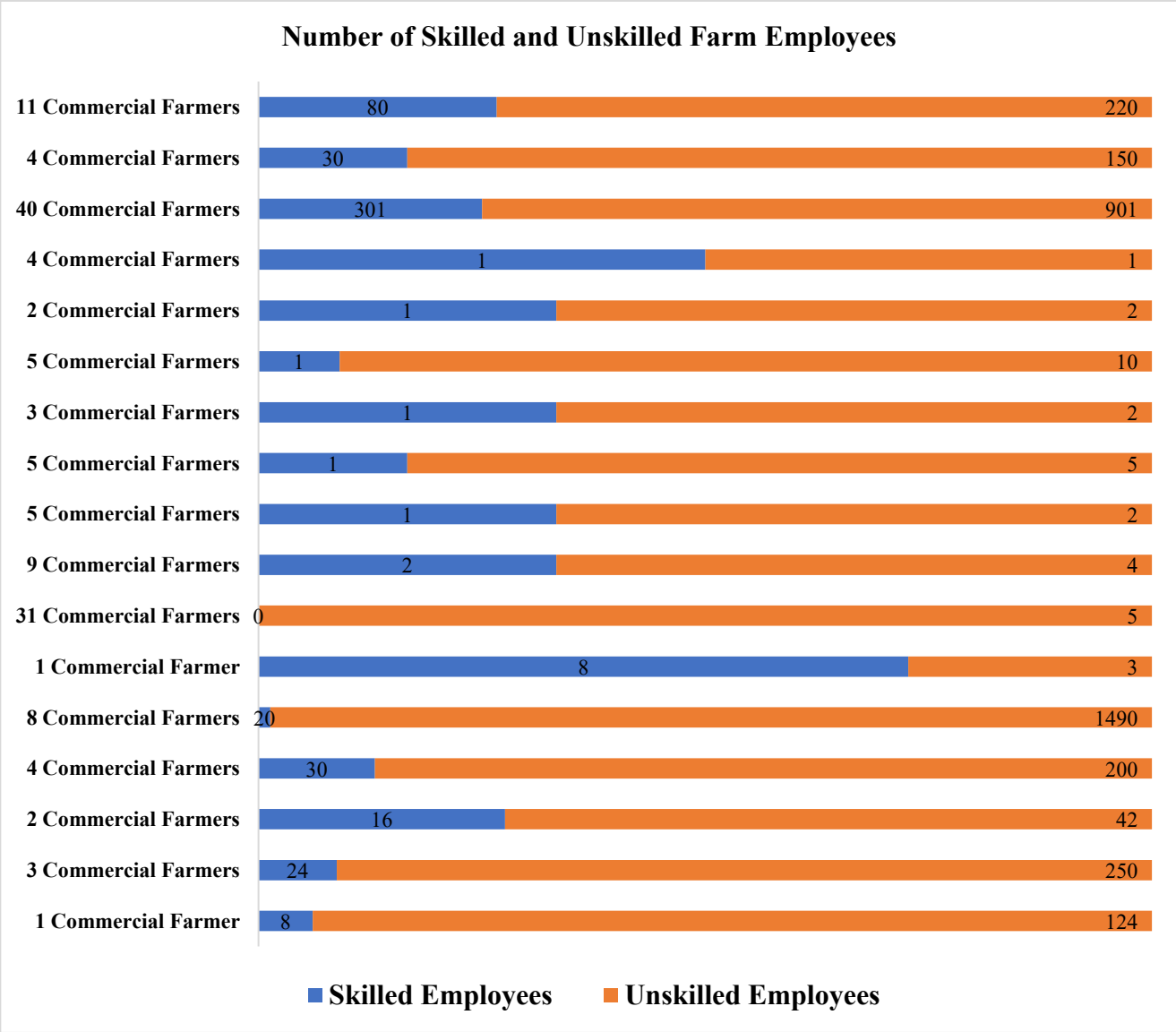
included Harvesters, Planters, Tractors, Vehicles, packing equipment, seed processing equipment, egg incubator, drip irrigation system, and Feed mills, while light devices were GPSs. “GPS on tractors, Combine Harvester, pivots, Computer controlled drip irrigation system, computer-controlled macadamia curing system, planters with sensors to indicate blocking” added one of them, and another explained that “Entire land prep and chemical spraying is done 100% by tractor drawn equipment. Fertigation, irrigation is fully automated, while harvest of all grain crops is by combine harvester. Potato harvest is by a tractor drawn harvester”.

4.2 Kind of commercial farms use automation

According to the respondents, automation is used for ploughing, irrigation, curing, computer recording keeping and digital scales, plant spraying and fertilization, and harvest. They added on that they use it for “Packing, grading, making Feed, distributing feed, and cutting grass”. They farm various kinds of crops and animals. The crops farmed include Seed Maize, Wheat, Barley, Macadamia nuts, Tobacco, Soya beans, potatoes, groundnuts, Pumpkin leaves, Popcorn, and sunflower. They said that also farm vegetables such as tomatoes, legumes, green pepper, chili, onion, beans, rape, Chinese rape, cabbages, and Nanga rape. Some farm fruits like blueberries and oranges. The animals farmed are “Cattle, Broiler Chickens, Sheep, and Wild game”, they added.

4.3 Skills affected by automation in agriculture sector

FIGURE 7: EMPLOYEE TYPE

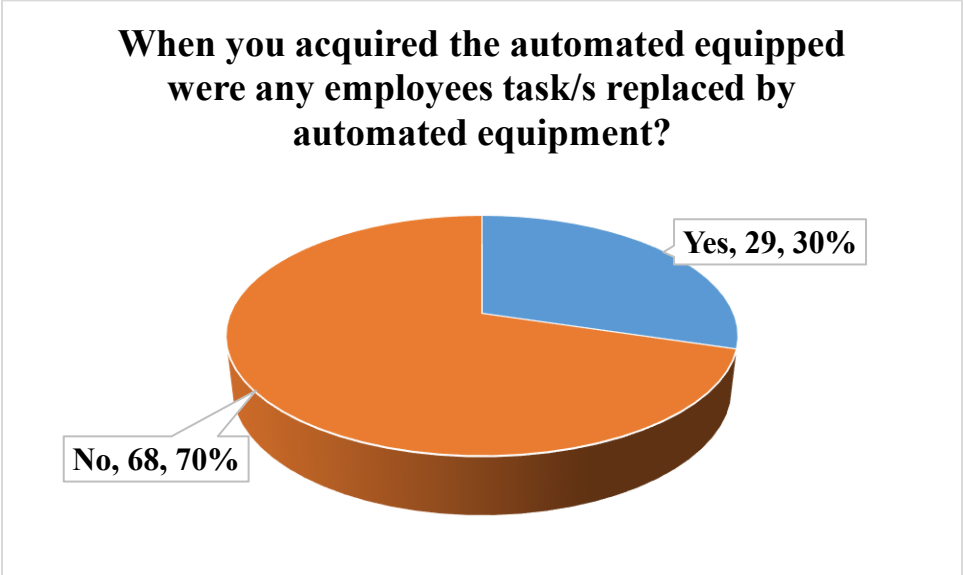


Source: Author (2022)

Of the 138 respondents, 28.8 % (40/138) of commercial farmers reported that they had 901 unskilled employees presenting a ratio of one skilled employee to three unskilled employees (1:3), whereas 21.7 % (30/138) had no skilled employees, and 5.8% (8/138) had 20 skilled employees against 1,490 unskilled employees (Figure 4.4).

4.3.1 Level of individual-skills affected by automation

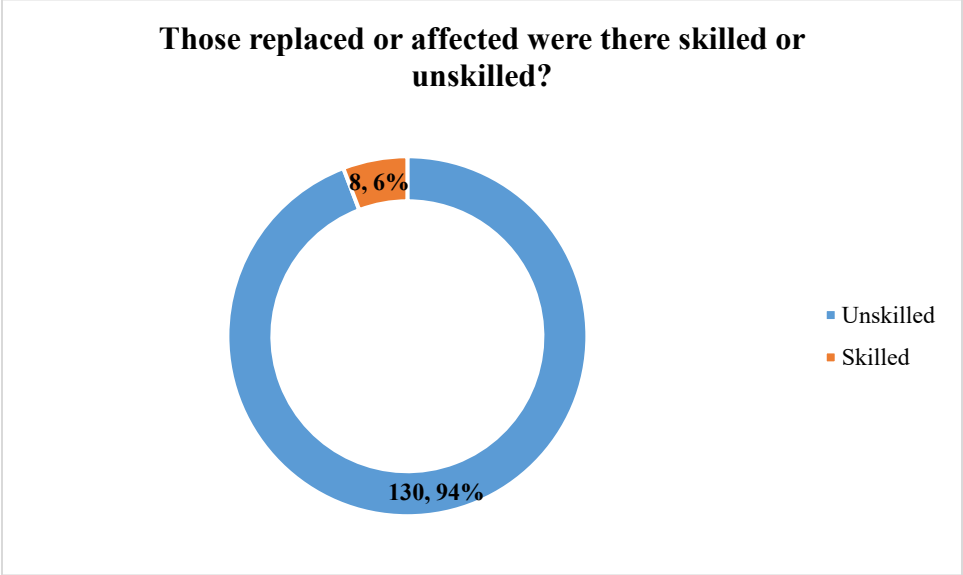
Figure 8: Loss of employment due to automated farming



Source: Author (2022)

4.3.2 Skill type affected automation farming

FIGURE 9: SKILLED TYPE AFFECTED WITH LOSS OF EMPLOYMENT DUE TO AUTOMATION OF FARMING



Source: Author (2022)

The use automation replaced, or displaced employees form farming employment as reported by 30% (29/97) commercial farmers (figure 4.5). There were 96 % (130/138) of respondents said that unskilled employees that were affected (figure 4.5.1). There were 1 to 100 employees that lost employment as reported by respondents, and one of the said that "around 40% lost employment upon acquisition and use of automated employment".

4.4 Effect that automation has brought on employment

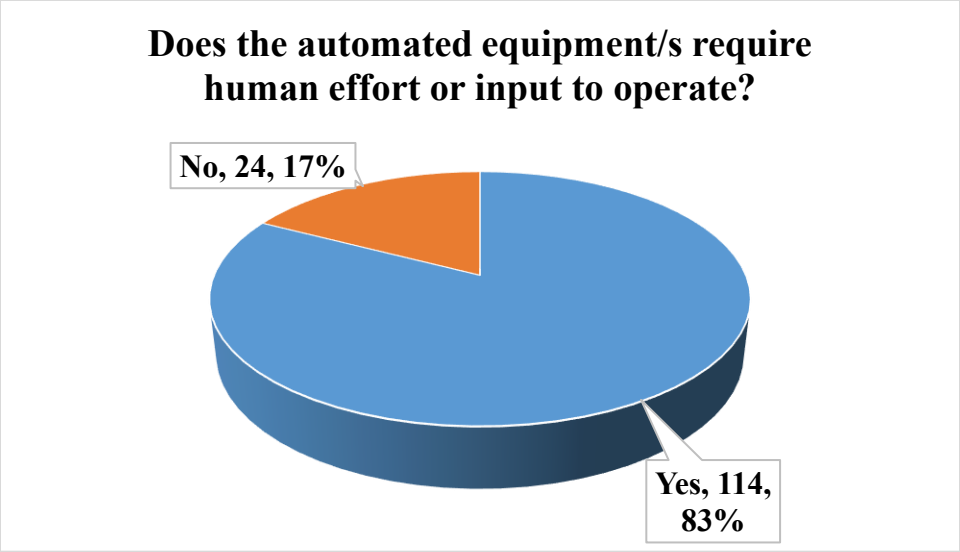
Table 2: Association between automation and unemployment

Automation	**Unemployment due to Replacement by Automation Use**			
	Replaced	Not Replaced	Total	Chi square test 3.9 Significance level
Use	49 (51%)	48 (49%)	97 (100%)	P = 0.049
Do not use	0 (0.0%)	41 (100%)	41 (100%)	P = 0.102 (Fishers' exact)
Total	49 (35.5%)	89 (64.5%)	138 (100%)	

Source: Author (2022)

4.4.1 Blending Automation and Human Effort

FIGURE 10: BLENDING AUTOMATION AND HUMAN EFFORT



Source: Author (2022)

The association between automation and unemployment was statistically on the borderline with a p-value of 0.049. The proportion of those that were replaced by automation to those that were not was 51% (49/97) to 49 % (48/97) respectively (table 4.2). On whether automation requires human input, or whether it is necessary to blend automation with human input, 83 % (114/138) said 'Yes' automated equipment require human input.

Although the 83 % (114/138) said 'Yes' automated equipment require human input, there were mixed experiences on the contention that automation farming is replacing human inputs in Zambia. The responses were Yes, No and not really. Those that said 'yes', explained that it is slowly and eventually replace human input especially the unskilled ones. They said it is unnecessary to have any people when few can do the work suing equipment. It is inevitable because if Zambia has to compete with the rest of the world farming must be modernised with less human input and specialised ones. They added on that "Yes, it is. Automation is by far more efficient, dependable, and much cheaper in the long term. The fewer the human element, the better". They further asserted that automation reduces on human resources issues and labour disputes with Trade Unions. There is no theft of crops when automation is used, there are no negotiations for improved working conditions. One of the respondents stated that "Automation takes away the headaches associated with negotiating worker's welfare and conditions of service with their Trade Unions, and dealing with the monthly statutory labour requirements." Others justified the use of automated farming that it is cheaper, reliable, and labour is becoming expensive.

Other respondents said no automation cannot replace human inputs because the advent of technology creates new skills and job opportunities. A respondent argued that "There's no way it can replace the entire workforce as these machines need people to operate them". Some added on that labour is still affordable. The same sentiments were expressed by those that said 'Not really'. "Not really because some of the automated equipment still has to be run by people". However, they observed that overtime automation will take over farming form labour as equipment increases. Those that are not skilled are the victims of losing employment due to automation of farming. A respondent opined that "The unskilled are being kicked out of the whole chain because they are not necessarily needed to do the work that machines can do".

4.5 Measures of reducing the effects of unemployment in the agriculture sector due to automation

4.5.1 Protection of Labour from Automated Farming

The suggestions on the protection of labour form automated farming are presented below under the following sections: labour and social security obligations, empowerment. Skills development, Local production over Imports, and value addition, and investments over jobs.

4.5.2 Labour and Social Security Obligation

The respondents said that labour would determine the saving of employment in the farming sector from automation. A number of commercial farmers still use intensive labour for various activities especially harvesting of maize by hand as well as other crops such as Macadamias. "Macadamias are reaped and picked up by labour, automation here will also be resisted if cost per kg stays reasonable". The demands of the Government through Labour office would push farmers to increase automation because labour would become expensive. Further, the enforcements of statutory obligations such as remitting of National Pension to the National Pension Scheme Authority (NAPSA) would also lead farmers to increase automation farming. The Government should reduce terminal benefits contribution to NAPSA. "Reduce terminal benefits. We are paying twice, once to NAPSA and again on termination of employment. This is a very good reason to automate", complained a Respondent.

4.5.3 Empowerment

More suggestions on the protection of labour from automation in farming indicated that, the government must empower the unskilled labour force with tasks that do not require equipment use. The unskilled population that would be loss jobs from farming must be supported as small-scale farmers and as small and medium entrepreneurs by the government. They must be empowered with start-up capitals "It therefore remains for government to turn those workers being replaced by machines into small scale farmers who will contribute to the national food basket. This can be achieved by having government facilitate access to affordable capital", said a respondent.

4.5.4 Skills Development

Apart from empower with capital, the respondents suggested that the unskilled labour face also require skills development. They require training on how to use machinery, and some must upgrade their skills. "Improve on skills development because mostly the unskilled lose jobs", said a respondent.

4.5.5 Local production over Imports, and value addition

They contended that labour can be protected from extinction in the farming sector by expanding the farming sector to increase local product. At the same time local production must be protected by stopping imports. More jobs will be protected in the sector when there is also an increase investment in value addition. "Increase farm numbers and production, create a food processing sector to export food, stop importing proteins into Zambia like mechanically deboned meat, this will automatically create more jobs. Imports are basically exporting jobs", suggested a respondent.

4.5.6 Investment over Saving Jobs

On the other hand, they said that as much as protection of labour from extinction is required in the farming sector, it cannot be done at the expense of investment, and meeting demand for global food. Automated agriculture has the potential to satisfy demand for global food and Zambia must automat to remain competitive on the global market. They said that "No investor, local or foreign, invests in any economic activity to create jobs for locals, hence the gravitation towards automation so they can make more money through heightened output. Unfortunately, government cannot force them to employ workers they do not need".

4.6 Chapter Summary

The chapter demonstrated that findings were generated as guided by the study objectives, and the objectives were attained by exhaustively presenting the findings in a concise and clear manner through charts and description summaries and excerpts from the respondents. The next chapter is a discourse on the study findings in contrast with other studies on the topic area.

CHAPTER 5

DISCUSSION OF STUDY FININGS

5.0 Overview

Chapter four presented key findings based on the study objectives with respondents' characteristics showing the background to the study setting. The researcher discusses key findings without using her pronoun but refer to the 'study'. Therefore, this chapter discusses the key study findings within the study context and in contrast with other studies on the topic area. The chapter preview provides an overall insight into the study settings which connects to the discussion of the study key findings. The chapter summary section ends the chapter presentation.

5.1 Preview

The study findings indicated that the mean age of respondents was 49 years with the youngest and oldest being 25 and 68 years respectively. This is fairly a young population involved in commercial farming which is energetic and well-schooled with generally holding BA or BSc degrees. A combination of age and academic qualifications are likely attributes of embracing technology easily. However, there were many unskilled farm employees despite having owners or farm managers with higher academic qualifications, with a ratio as high one skilled employee to three unskilled ones.

There was overwhelming response from commercial farmers from Chisamba as opposed to Mkushi, this is because most emails sent to commercial farmers in Mkushi failed to be delivered. This could be due to internet failure as Mkushi is relatively remote as compared to Chisamba. This though may not explain that farmers in Chisamba are more technologically advanced than those in Mkushi. The other reason could be that the online Google Form Questionnaire was distributed during festival seasons when farm administrators, Human Resources Managers, or Farmer owners were on break. Another reason could be that email addresses could have been changed because the failed not that there were no replies. Nonetheless, the response rate was good at 69.0%. The following sections discusses the findings as stipulated by the study objectives.

5.2 Kinds of automation used in agriculture sector

In regards to the first objective, the study established that most of the commercial farmers have mechanized their farming practice. There are 70.0% of commercial farmers using equipment to farm. This is in line with findings by Gaus and Hoxtel, (2020) study, that many countries on the continent are yet to implement earlier technological breakthroughs, including mechanization and digitalisation, on a larger scale. This effectively hinders most SSA countries from the introduction of advanced automation technologies. However, as explained in the preview, it is a clear indication that as much as most commercial farmers use automated equipment, they also use intensive labour alongside that because of the one to three ratio of skilled to unskilled labour. It must be noted that Gaus and Hoxtel, (2020) study inferred generally, this study was conducted among commercial farmers, in any case the findings are consistent with each other.

There were various kinds of equipment used by the commercial farmers. Heavy duty equipment such as combine harvesters, planters, tractors, Vehicles, packing equipment, seed processing equipment, egg incubator, drip irrigation system, and Feed mills as noted by Gaus and Hoxtel, (2020) study as well. These are operated by skilled labour which is a currently the global standard was such equipment are directly controlled by skilled individual though the fact is that there is no intensive labour required. Light equipment includes GPS which are installed on heavy equipment such as tractors and planter sensors.

However, although harvesting is done by combine harvesters some crops still use intensive labour to harvest. Clearly it is not because there is no technology yet for such but with time farmers would procure them. These findings show that automated farming in Zambia is to a great extent all-rounded, from land preparation to harvesting, even fumigation and irrigation though the presence of intensive labour is undeniably still there. Is the threat of displacing human labour looming? That is an eminent phenomenon, however, the rate at which this is taking place in Zambia is still unpredictable because in the midst of highly automated farming the presence of intensive labour is still strong. It must be started though that the study did not establish the frequency presence of intensive labour on commercial farms. The frequency could be just during harvest season or period which implies that most of the work is done equipment.

These findings clearly show that the level of automation use in Zambia's Mkushi and Chisamba farming blocks at same at the international ones. This evidence is reverberated by other studies that revealed that there are manifold of automation on the agriculture market, conventionally tractors are the main focus of point of entry for automation in developing countries (Adu-Baffour and Birner, 2019; Daun and Heni, 2020). Sectors such as aquaculture still use traditional methods (Maulu, 2019). However, automation in agriculture has advanced to a level of incorporating digitised devices. There are now robots that are codifiable (Millington, 2017) to drive tractors without a driver and to pick fruits and vegetables, and drones to monitor crops, detect specific soil and irrigation needs, ripeness of fruits and vegetables and health of animals (Gaus and Hoxtel, 2020).

Additionally, the study indicated that all kinds of commercial farmers use automated equipment especially those in crop farming. These include Seed Maize, Wheat, Barley, Macadamia nuts, Tobacco, Soya beans, potatoes, groundnuts, Pumpkin leaves, Popcorn, and sunflower farmers. Others are vegetable and fruit farmers. Equally, Guzueva et al., (2020) study show that automation is used for different kinds of farming such as in ranching and horticulture, Gaus and Hoxtel, (2020) Mukhalipi, (2018) and Daum and Birner, (2019) studies opined similar findings.

5.3 Level of individual-skills affected by automation

It has been indicated that the unskilled labour is proportionally high as compared to the skilled, however, the study established that only 30% were replaced due to automation of farming. This is not hue number though not as huge as it would be if automation were at full swing. Though it is a known fact that the unskilled labour are immediate victims of displacement by automation use in farming as shown by the study. In absolute numbers, the study illustrated that about one to 100 unskilled employees lost their job due to use of equipment in farming.

The findings sharply contrast with Millington, (2017) study findings that asserts that those that are highly trained and skilled are more likely to lose jobs to automation than the less skilled ones. The study further

observed that developing countries are more at risk than developed countries because that is where intensive labour is widely practiced. Millington, (2017) study simply agrees with Lima et al., (2021) study findings except that the two studies had limited insight on how automation would affect employment in the agriculture sector. Also, the studies underestimate the effect of automation in unskilled unemployment sector which is largely agriculture. Because vulnerability to automation is now based on whether jobs or tasks are codifiable and whether they are routine or not (Millington, 2017).

5.4 Effect that automation has brought on employment

Hypothesis test shows the rejection of the null proposition that automation use in agriculture does not replace human labour, it does. Notwithstanding that the probability value was a borderline. The rejection of the null hypothesis is justified by qualitative findings which shows a growing preference to automated farming now and the dawning future. This is despite the enthusiasm that automated farming will always require human input, thus blending farming is the future.

It is obvious that blending of automation and labour will favour the skilled employees, and ultimately many unskilled individuals will fall out of the sector. The main reason is that commercial farms are investors that look out for profits than saving jobs. They need efficient ways of production and automation is second to none. Apart from that, automated agriculture cuts on human resources and labour conflicts such as condition of services and meeting of labour statues and obligation such as paying pension fund which is expensive to farm owners and investors.

The debate on the influence of automation on labour are expressed by Gaus and Hoxtel, (2020) in agreement. The Gaus and Hoxtel, (2020) study concluded that automation a major threat to SSA workers. For the most part, the answer is no. At least not yet. The SSA countries, or significant parts of their economies, lack the infrastructure and capital for even a limited use of the automation technology discussed in this paper. Moreover, their informal economies consist largely of subsistence farmers, street vendors, and day labourers, and abundance of labour and, consequently, low pay make it cheaper to have human workers instead of robots or software doing the job. These findings indicate that SSA countries are in a dilemma because of what the emerged polarisaion between automation and intensive labour. The discourse of preferring the means of one form of production over the other is dependent over which one is cost effective and efficient. This poses a big human resource dilemma, except that the extent of automation in the agriculture sector in Zambia is not yet well understood or measured. The findings further agree with Lima et al., (2021) study findings, the study did not focus on agriculture, however, agriculture being the largest source of income around the world especially in low and middle income countries millions of people are likely to be unemployed when the transition to automation is scaled-up.

Can the jobs of unskilled labour force in the commercial farming sector be protected and how? The study findings showed that it is possible to do that but it requires adjusted interventions. Employment can be protected within the farming sector although not directly within the commercial farming in the advent of automation.

The study suggests that when labour continues to go up unskilled employees will continue losing jobs even at a higher proportion. The demands to meeting labour obligation from the Trade Unions and Labour office is likely to push the cost of labour higher which will make commercial farmers to transit to automated agriculture to reduce on labour conflicts. Is cheaper labour better than no job at all? Because why would

individuals work without social security? Because commercial farm investors are for profit not job creation as indicated and implied in the findings. In further agreement with study Lima et al., (2021) study, Lima et al., (2021)study suggests that technological unemployment can be curbed by tax reforms, negotiation for minimum income guarantees, reducing working week, and reforming higher education. What these solution entails is that human skills have become more expensive and automation is the cost-effective measure, as an alternative labour input.

The study findings differ with Millington, (2017) findings on the skilled labour being more threatened with job losses as compared to the unskilled one. Automation is the cost-effective measure, as an alternative labour input. Millington, (2017) study asserts that those that are highly trained and skilled are more likely to lose jobs to automation than the less skilled ones. The study further observed that developing countries are more at risk than developed countries because that is where intensive labour is widely practiced. Millington, (2017) study simply agrees with Lima et al., (2021) study findings except that the two studies had limited insight on how automation would affect employment in the agriculture sector. Also, the studies underestimate the effect of automation in unskilled unemployment sector which is largely agriculture. Because vulnerability to automation is now based on whether jobs or tasks are codifiable and whether they are routine or not (Millington, 2017).

The Guzueva et al., (2020) study adds to the discourse. The study recognised the importance of automation culture in present day agricultural activities. It provides a huge positive effect on the national economy of all countries implying its necessity, this sentiment is in tandem with the study filings. Innovation considers improved harvest creation by understanding soil wellbeing. It enables ranchers to utilize fewer pesticides on their yields. Soil and climate observing diminishes water squander. Advanced horticulture in a perfect world prompts financial development by enabling ranchers to get the most generation out of their territory. Ultimately, it helps economic growth pompously. However, the study also established forms of vulnerability among the low-skilled migrant labour community that are being replaced by automation technologies. This study rightly shows the effect of automation on agriculture employment, the study having been done in Russia, in a developed country. The Guzueva et al., (2020) study demonstrates the propensity trajectory of the automated agriculture in Zambia.

The findings by Murphy, (2020) study sounds hope of preserving jobs in the sector. The study asserts that despite the automated agriculture filling up the shortage in the agriculture sector it will not replace human intensive labour. Farming like horticulture and shearing still require labour intensive workforce. The report started that automation will continue to be blended with human-intensive workforce, as experienced by the Toyota Automobile which had replaced human power completely but later realized that the automation required human manpower workforce. These findings by Murphy, (2020) have been resounded in this study despite the context being different. This is because the developed countries are a model of moderation, and automation is simply the trajectory to that. Murphy, (2020) is also concurs with Liu, (2020) report The reported revealed that it should be ensured that robots and automated devices do not evolve to disrupt workers but to aid them and improve their working conditions. In fact, robots and automation might even help workers earn a higher salary, as many primary workers earn bonuses depending on volumes of harvest and how fast they can deliver their products. With most primary workers earning minimum wage, and illegal workers earning much less than that, robots and automation might help them to meet their bonus objectives without exposing themselves to unendurable physical pressure.

Gaus and Hoxtel, (2020) study confirmed that numerous technological advancements in the agricultural sector have increased productivity while decreasing the need for human labour, including driverless and autonomous tractors, fruit and vegetable picking systems, and drones for monitoring crops. However, most disruptive for the agricultural sector is the combination of self-learning autonomous robots doing manual work such as harvesting crops with sensors and pattern recognition that can detect soil specifics and irrigation needs, weeds, ripeness of fruits and vegetables, or animal health. This kind of technology obviously threatens jobs of the skilled labour force than the unskilled ones as show by the study findings in Zambia. However, it is certain that employment in the agriculture sector as in commercial farming are on crossroads.

Conversely, the Landmark Underwriting Agency (Pty), (2020) echo that the risks facing South African farmers such as weather-related incidents, rising input costs and the threat of violent crimes are likely to lead to increased automation in the local agricultural industry. This is rather interesting because literature consistently indicate that labour-intensive costs push investors in agriculture adopting automation-intensive, which is what this study has indicated, that apart from price of labour, theft and labour conflicts would push farmers to automate. At the same time the report stated that the other reason for possible transition to automated agriculture will be the demand for increased minimum farming wages combined with energy hikes in electricity and fuel.

5.5 Measures of reducing the effects of unemployment in the agriculture sector due to automation

The study revealed that, the effects of automation on employment can be salvaged by empowering the unskilled labour force in agriculture. The unskilled employees are usually scale farmers themselves. These need to be empowered with capital to sustain their farming activities. Small scale farmers are known to have contributed to national food security therefore, with the looming takeover of automation in farming they must be prepared to grow their farming not only by provision of capital but also imparting them with skills. They require training on how to use the equipment which threatens their employment. The unskilled employees must be given skills to even use in their farming endeavour.

Further protection of employment of unskilled labour forced could be secured by restricting imports of farm produce that are produced locally. Imports kill local markets from cheap imports and this in turn affects profitability of farmers and need for cutting cost, the victim is reduction in labour required. There must be investment in agribusiness to take up more of labour force from the primary agriculture. When jobs are diminishing in the primary agriculture, the agribusiness would employ them. This also requires imparting of skills in agribusiness. Agribusiness serves as a forward and backward linkage loop in agriculture, and it is a value addition sub-sector.

Similar, recommendations were provided by Mukhalipi, (2018) study which indicated that the future of technology advancement, automation in the agriculture sector might disrupt economic and social activities in developing countries including Zambia by the year 2026. The review recommended that development strategies on human capital development should address the challenges associated with low labour productivity and how technological advancements, automation in the service sector will sustain jobs that Zambian Government will have created for the locals by the year 2026. It further stated that development strategies on human capital development which will ensure that most workers which enter

the labour force after dropping out of school, attain basic numeracy, Information, communication and Technology and literacy skills by 2026.

In view of these findings, the Researcher proposed prototype model indicated below as discussed in the themed sections above.

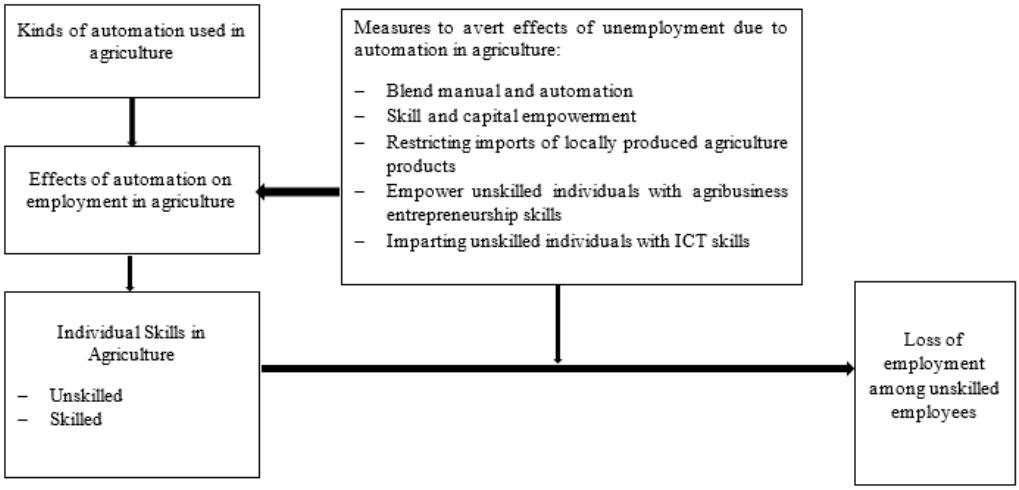


FIGURE 11: MODEL TO AVERT LOSS OF EMPLOYMENT IN AUTOMATED AGRICULTURE

Source: Author (2022)

5.6 Implication

Agriculture automation is directly replacing manual human resource especially those with limited skills, and the push for statutory obligation is exacerbating commercial farmers to adopt agriculture automation. This means that although blending is an alternative to save manual labour, eventually most of the employees or labour force will be replaced in the sector in Zambia because commercial farmers are fate profit making as opposed to crating employment.

5.7 Chapter Summary

Chapter five discussed the findings in the context of the study setting and the findings were further contrasted with other studies on the topic area. The study findings and discussion were based on a representative sample size to the target population and the findings showed consistency with a number of other study findings. The next chapter makes conclusions and recommendations on key study findings.

CHAPTER 6

CONCLUSION AND RECOMMENDATIONS

6.0 Introduction

Chapter five discussed the study findings within it context and by triangulating with other study findings. This chapter makes conclusion on key study findings as outline by study objectives. Additionally, the chapter makes recommendations on the study findings.

6.1 Conclusions

6.1.1 Kinds of automation used

The study established that most farmers in Mkushi and Chisamba use automated devices to farm and these including both heavy and light equipment. Automation is used by various kinds of farming vegetable, fruit, crop and animal farming.

6.1.2 Level of individual-skills affected by automation

The growing use of automation in agriculture largely affects employees that are unskilled in the two districts and commercial farms employee unskilled labour despite increasing use of automation. About one-third of unskilled employees were affected by loss of employment due to automation.

6.1.3 Effect that automation has brought on employment

The study further indicated that automation has effect on job security of farm employees. However, currently despite some employees being replaced by automation there is blending of equipment and intensive labour. Moreover, the association between automation and employment was statistically insignificantly a borderline; implying effects are on a cross as farmers are gradually incorporating automation replacing intensive labour in various farming activities.

6.1.4 Measures of reducing the effects of unemployment in the agriculture sector due to automation

Furthermore, the study proposed that reducing labour and social security obligations, empowerment, Skills development, substituting imports with local production, and value addition. Although, investors in the farming sector prefer profits over saving jobs.

6.2 Recommendations

The study recommends the following:

6.2.1 Kinds of automation used

The commercial farmers in Mkushi and Chisamba should continue to blend automation and intensive labour to save the much needed jobs by the local people.

6.2.2 Level of individual-skills affected by automation

Commercial farmers must orient the unskilled employee with automation skills in farming so that the skills can be applied elsewhere when the lose jobs.

6.2.3 Effect that automation has brought on employment

The Ministry of Agriculture and Ministry of Commerce and Industries must encourage unskilled employees in agriculture to form cooperatives and learn use of automated equipment and provided with grants to start up agri-businesses.

6.2.4 Measures of reducing the effects of unemployment in the agriculture sector due to automation

- The Ministry of Labour and Social Security and National Pension Scheme Authority must find win-win situation of engaging commercial farmers in meeting their obligation for their employees.
- Further, farm employees must be empowered and provided with Skills development
- The Ministry of Finance and Ministry of Commerce and Industries must restrict the imports of products that are locally produced by farmers to save among the of local employees
- The Ministry of Commerce and Industries must design interventions to engage local people around commercial farms to engage in agri-business through cooperatives which would provide backward and forward linkages for commercial farmers.

6.2.5 Future Studies

Future studies must establish the effects of job losses due to automation among the persons that lose the jobs or the employees that lose jobs.

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APPENDIX A: INTERVIEW GUIDE

BRIEF INFORMATION ABOUT THE STUDY

My name is Chibuye Dorica Sitali, student number GSB 151315 from the University of Zambia Graduate School of Business Studies pursuing a master's degree of Master of Science in Human Resource Management. I am currently carrying out research titled "The Effect of Automation on Employment in the Zambian Agriculture Sector" which is a partial fulfilment required for the award of the degree. You have been identified as one of the respondents for this study, which is purely academic, thus am requesting for your permission as a Human Resource Manager/Officer to fill out this Interview Guide. The study is highly confidential as no personal identifiers will be collected or linked to the data you will provide. There is also no risk involved taking part in the study. Your anonymity, autonomy and respect will be highly upheld and you will be allowed to decide to discontinue or continue taking part in the study at any time you want without any repercussion. Filling out the interview guide will take approximately 5-15 minutes, there is no compensation for the time taken to fill out the interview guide; your participation is absolutely voluntary, based on your goodwill.

Kindly contact me for any information or clarification using my mobile number +260 0961 082 208 or email address: sitalichibuye@gmail.com. Your support is highly appreciated.

SECTION A: RESPONDENT BACKGROUND DATA

How old are you? [ ]

What is your gender?

Male [1]

Female [2]

What is your highest level of academic qualification?

Grade Nine [1]

Grade Twelve [2]

Diploma [3]

Degree [4]

Maters' Degree [5]

PhD [6]

How long have you been working at this farm? [ ]

How many employees do you have? [ ]

How many are skilled and unskilled employees?

Skilled [ ]

Unskilled [ ]

What crops do you farm or produce here?

SECTION B: TYPES OF AUTOMATION

Do you use any automated equipment to produce or farm the crop?

No [1]

Yes [2]

If yes, what kind of automated equipment/s do you use?

What do you use them for in the farming process?

Does the automated equipment/s require human effort or input to operate?

No [1]

Yes [2]

When you acquired the automated equipped where any employees task/s replaced by automated equipment?

No [1]

Yes [2]

If yes, how many were replaced? [ ]

Those replaced or affected were there skilled or unskilled?

Skilled [1]

Unskilled [2]

From your experience and views, is the automation/digitalisation of farming replacing human inputs in Zambia, kindly explain how?

What type of skill/S have been lost as a result of automation or digitalisation?

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What should be done to protect humans working in the farming sector from being replaced by automation/ digilisation in Zambia?

End the interview and thank you for taking part