STEM PROGRAM CHARACTERISTICS AND LABOUR MARKET OUTCOMES OF GRADUATES OF NATIONAL POLYTECHNICS IN KENYA

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A Thesis Submitted to the School of Education in Partial Fulfilment for the Requirements of the Award of the Degree of Doctor of Philosophy in Economics of Education of Masinde Muliro University of Science & Technology

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DECLARATION

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CERTIFICATION

The undersigned certify that they have read and hereby recommend for acceptance of Masinde Muliro University of Science and Technology, a thesis entitled **'STEM Program Characteristics and Labour Market Outcomes of Graduates in National Polytechnics, Kenya'**

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DEDICATION

This work is dedicated to my wife Dr. Elizabeth Murey, my mother Beatrice Angehi, my father, the late Samuel Jahonga, my daughters, Charity, Joy, and Hope and all students in TVET institutions in Kenya.

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ABSTRACT

Recent developments and focus on technical education in Kenya have witnessed exponential growth in student enrolment, funding as well as increased number of TVET institutions. Training in Science, Technology Engineering and Mathematics (STEM) programs in these institutions aims at increasing creativity, innovativeness, and entrepreneurial activities that would address the industry skill gap, unemployment and reduce job search duration among graduates. However, unemployment among the youth in Kenya continues to be a persistent problem. The global youth unemployment stands at 5.8% while in Kenya, youth unemployment increased from 7.31% in 2016 to 13.84% in 2022. The goal of this study was to assess the effect of STEM program characteristics on the labour market outcomes of graduates of selected national polytechnics (NPs) in Kenya. The study's specific objectives were to establish the effect of the; nature of STEM academic programs, the level of STEM academic programs, the academic field of study, and STEM academic program's teaching resources on the labour market outcomes of graduates. The study was anchored on the job search and job competition theories. Based on pragmatic philosophical underpinning, the study adopted a mixed method approach utilizing a sequential explanatory design. The study targeted the 2016 cohort of STEM NPs graduates, 11 registrars, and 11 office of careers services officers. Stratified simple random sampling, snowball sampling and purposive sampling techniques were used to get the sample population. A sample size of 1834 respondents was sampled from a target population of 21151. Telephone interviews, focus group discussions, and interview schedules were used to collect data. Data was analysed both qualitatively and quantitatively. Logistic regression model, multinomial logistic regression, survival analysis, and structural equation model tools for inferential statistics were adopted. Findings revealed that graduates who pursued modular programs had a higher hazard rate compared with non-modular. Through the interview, it was revealed that shift towards modular courses is driven by the need to align training with industry demands and the evolving workforce. The employment survival probabilities of graduates reduced to 22% over the 65 months. The diploma graduates exhibited a higher hazard rate compared to other certification levels. Respondents with higher diploma and craft certification had a median time to employment of approximately 52 months (95% CI: 49.4-54.6), while those with artisan certificate had a median time of approximately 62 months (95% CI: 58.9-65.1). The time to employment varied significantly across the four certification levels. Focussed Group Discussion revealed that practical skills and personal attributes are crucial for securing employment in technical fields. Employers, particularly in the private sector, value hands-on experience and practical competencies more than academic qualifications. Job seekers need to demonstrate both mastery of skills and confidence in their abilities to be successful. Training Resources had a significant indirect effect on Employment category ($\beta = 0.169$, $T = 7.272$, $P = 0.000$. The study concludes that the nature of STEM academic programs significantly affects labour market outcomes for graduates, with modular programs leading to higher earnings and faster job placements compared to non-modular programs. Diploma graduates also experience better job prospects, with a higher hazard rate for employment. The academic field of study impacts earnings, with graduates from Health Sciences, Agriculture & Environmental Studies, and Electrical & Electronics Engineering earning more than those from other fields. Improved accessibility to educational resources is linked to better employment outcomes. The study recommends improvement of employment outcomes for STEM graduates in order to promote self-employment by offering entrepreneurial training and resources, and to create a supportive environment for the public and private sectors to absorb more youth. Training institutions should facilitate academic progression from Artisan to Craft to Diploma levels. Expanding job placement services with personalized support, such as resume writing and interview preparation, can reduce job search duration.

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OPERATIONAL DEFINITION OF KEY TERMS

Academic program teaching and learning resources	Teaching resources that include; access to institutional academic facilities, curriculum resources, and careers services
Academic Program performance	Graduate's pass or fail in a summative exam
Accessibility	Ease with which respondents had access to workshops, laboratories, equipment and other teaching resources
Artisan	A level of a program whose entry grade is a Kenya Certificate of Secondary Education grade D- or less
Craft Certificate	A level of a program whose entry grade is a Kenya Certificate of Secondary Education grade D (Plain) or D (Plus)
Diploma Certificate	A level of a program whose entry grade is a Kenya Certificate of Secondary Education grade C (Minus) and above
Fail	An examination grade of a Refer in one or two papers or "Fail" in more than two units
Field of study	Aarea of study such as; Agriculture & Environmental Studies, Applied Sciences, Building & Civil Engineering, Electrical & Electronics engineering, Health Sciences,

	Hospitality & Institutional Management, Information & communication, Technology and Mechanical Engineering
Graduate	Any student of the 2016 cohort who has done a STEM CDACC or KNEC summative exam. Such students may have passed or failed the exam
Higher Diploma Certificate	A level of a program whose entry grade is a Diploma
Labour market outcomes	Employed in the area of study, Employed in a different area of study, Self-employed in the area of study, and Self-employed in different area, not employed), Earnings, sector employed (Public/Private) and mean duration of job search that reflect the economic prospects of respondents in the labour market
Level of academic program	Artisan, craft, diploma and higher diploma levels
Modular program	A training program in which training content is divided into modules that have complete and independent units.
Nature of academic program	Modular or non-modular programs

Non-Modular Program	Traditional KNEC program that has one summative examination usually at the end of 2 years for Craft programs and 3 years for diploma programs.
Pass	Examination grade score of "Pass with Distinction", or a "Pass with Credit", or a "Pass".
STEM	A training approach that is; hands-on(practical), inquiry-based, project-based, research based, technical skills based, collaborative learning, team work based, technology based and lays emphasis on creativity, innovation and problem-solving.
Social network	Is a set of relationships that link NP graduates with other respondents and organizations/industry

LIST OF ABBREVIATIONS AND ACRONYMS

AfDB	African Development Bank
AIC	Akaike Information Criteria
APA	American Psychological Association
BIC	Bayesian Information Criterion
BLS	Bureau of Labour Statistics
CBC	Competency Based Curriculum
CBET	Competency-Based Education Training
CDACC	Curriculum Development, Assessment, and Certification Council
CDF	Constituency Development Fund
CEDEFOP	European Centre for the Development of Vocational Training
CPD	Continuing Professional Development
EU	European Union
FGD	Focussed Group Discussion
GGGI	Global Gender Gap Index
GMAC	Graduate Management Admission Council.
GoK	Government of Kenya
HESA	Higher Education Statistics Agency
HOD	Head of Department
HTMT	Heterotrait-Monotrait Ratio
ICSE	International Classification of Status in Employment
ICT	Information Communication Technologies
IEA	Institute of Economic Affairs

ILO	International Labour Organization
JSI	Job Search Intensity
KILM	Key Indicators of Labour Market
KIPPRA	Kenya Institute for Public Policy Research and Analysis
KNBS	Kenya National Bureau of Statistics
KNQA	Kenyan National Qualifications Authority
KSTVET	Kenya School of TVET
KTTC	Kenya Technical Training College
MoE	Ministry of Education
NACOSTI	National Council of Science, Technology and Innovation
NCSES	National Centre for Science and Engineering Statistics
NEET	Not in Education, Employment, or Training
NP(s)	National Polytechnic(s)
OECD	Organization for Economic Co-operation and Development
RRR	Relative Risk Ratio
SA	South Africa
SDG	Sustainable Development Goals
SDI	Skills Development Scheme
SDVTT	State Department of Vocational and Technical Training
STATA	
STEM	Science, Technology, Engineering and Mathematics
UNESCO	United Nations Educational Scientific & Cultural Organization
TVET	Technical Vocational Education and Training
TVETA	Technical Vocational Education and Training Authority

VET	Vocational Education and Training
VTT	Vocational and Technical Training
WB	World Bank
WEF	World Economic Forum

CHAPTER ONE

INTRODUCTION

1.0 Overview

This chapter presents the framework from which the study is based. It seeks to bring to the core, the concept of labour market outcomes. Other key issues discussed in the chapter include: the background of the study, statement of the problem, objectives, research hypothesis, justification, significance of the study, scope of the study, limitation of the study and theoretical/ conceptual framework.

1.1 Background to the Study

The basis of STEM-education is the integration of science and mathematical disciplines with the engineering and technical ones – "STEM disciplines" (mathematics, physics, chemistry, biology, engineering, computer science, astronomy, and geography), (Morze & Strutynska, 2021). Technical and Vocational Education and Training (TVET) connects education and the world of work, unlocking the potential of young people and adults for a brighter future (Magadza & Mampane, 2024). Yet, it is estimated that 267 million young people are not in employment, education or training (UNESCO, 2022). TVET has occupied a prominent position in the international development agenda driven by institutions such as the World Bank and the International Labour Organization (ILO), (Powell & McGrath, 2019; Allais & Wedekind, 2020. Despite the growing prominence of TVET, its full potential remains untapped, particularly in addressing the needs of youth unemployment (Olayele, 2022).

The UNESCO strategy 2022-2029(UNESCO, 2022) seeks to promote skills development for empowerment, employment, and decent work, aiming to drive digital, green and inclusive economies. The organization supports TVET transformation in all member states and collaborates with global partners to prioritize TVET in education (Galguera, 2018). These collective efforts are necessary to equip youth and adults in acquiring new skills, to unlock the potential to successfully navigate the social, economic, and environmental changes which the world is undergoing (Galguera, 2018; Semali, 2024).

Labour market outcomes include indicators such as earnings, sector of employment, employment status, and unemployment duration (Aronson et al., 2024; MacKay et al., 2024). These outcomes may vary by region, shaped by economic trends, technological changes, demographic shifts, and educational systems (Bol et al., 2019; Eberhard et al., 2017).

Globally, labour markets show disparities in wages and employment types (Guerriero, 2019; Stockhammer,2017). High -income nations like North America and Europe have higher wages due to technology, education, and labour regulations (Hoeven, 2019; Kaplinsky & Kraemer-Mbula, 2022). In contrast, lower-income countries, especially in Sub-Saharan Africa and Asia, face income inequality, with many workers in informal or low-wage sectors (Grimshaw & Bustillo, 2016). The COVID-19 pandemic worsened income gaps, as tourism sectors lost jobs, while technology industries thrived (Țîrcă, et al, 2021).

High-income counties are shifting towards service sectors like finance, healthcare, and technology due to technological advances (Ghani & O'Connell, 2016; Ng-Kamstra, 2016). Vilkas et al., (2022) observe that globalization has contributed to service-oriented economies in developed nations. Developing economies remain reliant on agriculture and extractive industries, though there is a gradual shift toward services and manufacturing, especially in urban areas (Oyelaran-Oyeyinka, & Lal, 2022; Ström, 2024).

Employment status is evolving, with more part-time, temporary, and gig economy roles in high income countries (Kuhn & Galloway, 2019; Manyika et al., 2016; Vilkas et al., 2022). In low-income countries, informal employment dominates, with over 60% of workers lacking formal contracts or social protections (ILO, 2023; Plagerson et al., 2022; Stuart et al., 2018). Informal work leads to income volatility and poor conditions, making it difficult for workers to escape poverty (World Bank, 2022; ILO, 2022). Youth unemployment is a global issue, with young people facing long job searches due to skills mismatch (OECD, 2022; UNDP, 2023).

Africa's labour markets are shaped by youth population growth, urbanization, and reliance on agriculture (ILO, 2023). Despite a young workforce, high youth unemployment persists due to slow industrial development and political instability (Losch, 2016; AfDB, 2022; UNDP, 2023). Africa's earnings vary significantly with higher wages in North-Africa which has a larger manufacturing and services sector compared to Sub Saharan Africa, which is reliant on low-wage agriculture (Modi, 2019; Odusola, 2017). Gender wage disparities are a common particularly and informal sectors where women are overrepresented (ILO, 2023; UN Women, 2022). These disparities limit economic mobility particularly for women (UNDP, 2022).

The informal sector employs over 80% of Africa’s workforce, particularly in rural areas (ILO, 2023). Informal workers face income instability and poor working conditions, while the gig economy offers both opportunities and challenges (Losch, 2016; Woldemichael et al., 2019). Despite these challenges, informal employment remains a critical source of livelihood, leaving workers vulnerable to economic shocks (Bassier et al., 2021; Linh, 2024).) Additionally, youth unemployment is the highest globally, with many young people discouraged after long job searches (Donkor, 2021; Baah-Boateng, 2016).

Kenya's labor market faces challenges in earnings, employment status, and a skills gap (Filmer & Fox, 2014; Fox et al., 2016). Urban centers like Nairobi offer higher wages in sectors like finance and technology, while rural areas remain dependent on agriculture, which offers lower wages (Beyeret al., 2016; Gore, 2018). These disparities are exacerbated by limited access to education and training (Botwinick, 2017).

Youth unemployment in Kenya remains a pressing issue, exacerbated by a mismatch between education and labour market needs (Kippra, 2021). Despite economic growth, many young people, particularly graduates, struggle to secure formal employment due to a lack of relevant skills and experience (UNDP, 2022; ILO, 2023).

According to Kefalis and Drigas (2019), STEM teaching prepares students for the world of work. Its main goal is not to educate intellectuals in the classical sense, but professionals with the specific knowledge and the chance to satisfy the needs of the labour market (Alter & Kocsis, 2021).

In Kenya, the government has increased its focus on TVET education in Kenya (Sifuna, 2020). This has resulted into a steady rise of student enrolment in TVET institutions (KNBS, 2022). These efforts have been motivated under the assumption that TVET education is a panacea for youth unemployment and job creation in Kenya (Ngware et al., 2024).

The educational reforms aim at ensuring that the youth are actively involved in the economic activities of the country through innovative and creative ways of job creation (Ouko, et al., 2022). It is however noted that unemployment in Kenya especially among the youth is high (Khainga, & Mbithi, 2018). The concern for any youth today is whether education continues to play a role in securing job opportunities and better economic welfare (Woessmann, 2016).

The unemployment rate of tertiary education graduates in comparison with other non-tertiary education graduates is the lowest (Stojanová & Blašková, 2014). The success of graduates in the transition from college to work does not bring just material satisfaction, but also social contacts, access to network building, the possibility to find a job, development of skills, and space to gain new experience (Weerdt et al., 2024).

The concern in TVET training is in its efficacy to provide relevant skills that are fit for the job market (Okolie et al., 2020; Chukwu et al., 2020). Specifically, are the national polytechnics producing required human resources that are capable of meeting industry needs? The alignment between curriculum design and industry requirements of NPs programs is a necessary requirement to produce graduates with competencies necessary to thrive in the workforce and meet sector-specific demands (Meunmany, 2024; Sharma, 2017).

In order to meet industry requirement needs, labour market information and gathering intelligence on current and future skills is necessary (Akyazi et al., 2020; Suarta et al., 2017; Li, 2024). Such information can inform training institutions on how to train for jobs and yield better labour market outcomes among the youth in Kenya. The challenge of youth unemployment has been influenced by the growth of the working-age population in Africa (Baah-Boateng, 2016).

According to the African Development Bank (AfDB, 2019), the continent's youth population is projected to increase by 105 million people by 2030 with 94 million living in the sub-Saharan region (ILO, 2020). In Kenya, the youth constitutes 30% of the total population while youth unemployment constitutes 78% of total unemployment (Ouko, 2022). The World bank noted that unemployment rate rose from 10.26% in 2018 to 13.84% in 2021 (WorldBank, 2022). This menace of unemployment poses a greater risk to the growth and strength of this country (Pink, 2018).

1.2 Statement of the Problem

Kenya's education policies have consistently aimed to enhance the relevance, quality, and accessibility of education guided by Vision 2030 which focuses on social political, and economic development to achieve middle-income status by 2030 (GoK, 2013b). A key component of this vision is the promotion of Science Technology Engineering and Mathematics (STEM) through increased investment in STEM to enhance creativity, innovation, and employment among graduates. The recent emphasis on technical vocational education & training (TVET) is evidenced by higher student enrolment, increased funding, and the growing number of TVET institutions suggesting potential benefits from this investment. The supply of TVET graduates in the Kenyan labour market highlights significant issues related to workforce dynamics and skill alignment. Despite an increase in the number of TVET graduates, there is a noticeable gap between the skills these graduates acquire and the needs of the labour market. This gap points to a challenge in ensuring that TVET training programs effectively address the evolving requirements of industry. Despite these efforts, unemployment in Kenya remains a critical issue with the rate rising from 7.31% in 2016 to 13.84% in 2022 (OECD, 2023). While the global youth unemployment stood at 5.8%. There is need to establish the impact of TVET education on labour outcomes (OECD, 2010; ILO, 2020; OECD, 2011; Awad, 2020) . The central concern of this study is whether TVET institutions particularly national polytechnics are effectively producing graduates with skills that align with the labour market demands and contribute to job creation. Despite the expansion of TVET training, Kenya's labour market faces persistent skill shortages, particularly in STEM fields (Kippra, 2021). This study sought to assess whether TVET expansion has addressed these issues and evaluate if the nature of the course, level of academic certificate and the field of study have effect on earnings, employment status, employment sectors, and unemployment duration.

1.3 Purpose of the Study

The purpose of this study was to establish the effect of STEM program characteristics on labour market outcomes of graduates of National Polytechnics in Kenya.

1.4 Objectives

i. To establish the effect of the nature of STEM academic programs on labour market outcomes of graduates of national polytechnics in Kenya.
ii. To determine the effect of the level of STEM academic programs on labour market outcomes of graduates of national polytechnics in Kenya.
iii. To assess the effect of the academic field of study on labour market outcomes of graduates of national polytechnics in Kenya.
iv. To evaluate the effect of academic program teaching and learning resources on labour market outcomes of graduates of national polytechnics in Kenya.

1.5 Research Hypothesis

This study was guided by the following null hypotheses which were tested at alpha 0.05:

$H_0$1: The nature of STEM academic programs has no statistically significant effect on the labour market outcomes of graduates of national polytechnics in Kenya.

$H_0$2: The levels of STEM academic programs have no statistically significant effect on labour market outcomes of graduates of national polytechnics in Kenya.

$H_0$3: The STEM academic fields of study have no statistically significant effect of on the labour market outcomes of graduates of national polytechnics in Kenya.

$H_0$4: The STEM academic program teaching resources have no statistically significant effect of on labour market outcomes of graduates of national polytechnics in Kenya.

1.6 Significance of the Study

Information on the labour market outcomes is the backbone for education and employment strategy for national polytechnics in Kenya, other TVET institutions, educationists, employers, industry players, and other stakeholders in the sub-sector. This information will be valuable for evaluating the results of training in the NPs within the context of relevance to industry requirements. Insight into the effect of the nature of STEM programs and the labour market outcomes will give important feedback on the effect of the modularization of academic programs on employment outcomes against non-modular programs. Students of national polytechnics, parents, and educational practitioners within the TVET subsector will make informed choices on the relevance and marketability of programs being developed and implemented.

Labour market information on the effect of the level of STEM academic programs and labour market outcomes are important indicators to admission officers, careers guidance officers and learners in planning and recruitment of students into academic programs. Findings of the study on effect of STEM academic program performance and labour market outcomes are important signals to potential employers and other labour market players. Graduate's academic credentials may signify to employers a specific pathway of achievement or performance, as well as the future performance potential. This will further play a significant motivating factor to students to work on their academic productivity while studying and preparing for their examination.

Access and availability of adequate teaching resources determine the quality of graduates produced and their chances of having a competitive age on labour market outcomes. In summary, this study will inform training institutions managers in NPs and other relevant stakeholders to constantly review and monitor the external efficiency of their training systems in order to make programs match industry demands and fit for the labour market.

1.7 Assumptions of the Study

This study made the following assumptions: First, the expected skills acquired by TVET graduates from all the national polytechnics were homogeneous across similar levels and the nature of programs. This was to give graduates of all 11 NPs an equal chance for labour market outcomes. Further, some predictors of academic program choice and labour market outcomes were typically unobserved or poorly measured because of the causal vocational effect on outcomes (Brunello & Lorenzo, 2017; Diaconu, 2014).

Secondly, the decision to accept/reject a job offer depended on the minimum wage/salary potential employees were willing to take up. This was the reservation wage. This reservation wage was assumed to be the same for graduates of the same level of qualification. Thirdly, the decision to take up a job offer also depended on whether potential employees were willing to relocate from their current place of residence to a new location where they found the job. Such decisions included family responsibilities and living expenses among others. This relocation cost and the associated opportunity cost were assumed to be the same for all graduates. Fourth, the labour market faced a perfectly competitive market structure where many other job seekers and workers could freely enter and exit employment.

Lastly, the study period constituted a labour market shock in the year 2020 when we had the world Covid-19 pandemic. The study assumed that there was no labour shock owing to the Covid-19 pandemic and that the labour market effects of employment, reemployment, or other characteristics such as job opportunities available were equally the same for all the graduates.

1.8 The Scope of the Study

This study was limited to 10 National Polytechnics and Kenya School of TVET, formerly Kenya Technical Trainers College (KTTC), for the 2016 STEM cohort (joined in 2016) and completed their programs at craft, diploma, and higher diploma levels in the period 2017 - 2018. These graduates are expected to have joined the labour market between the period January 2017 and December 2022 when this study ended. The period of this study is therefore limited to January 2016 and December 2022. The 2016 legal notice that established the NPs in Kenya led to higher student enrolment, more funding, and the mandate to be qualification-awarding institutions.

This study focused on graduates who had been in the labour market for at least five years since 2017. The polytechnics included Kenya Technical Training College, Kisumu National Polytechnic, Eldoret National Polytechnic, Meru National Polytechnic, North-Eastern National Polytechnic, Kenya Coast National Polytechnic, Kitale National Polytechnic, Kisii National Polytechnic, Kabete National Polytechnic, Nyeri National Polytechnic, and Sigalagala National Polytechnic. Graduates of the 2016 cohort who pursued STEM programs were included in the study. The study also focused on the Registrars and Careers Coordinators. Data collection was undertaken between April 2023 and June 2023. The study only sought to establish the effect of STEM programs' characteristics and labour market outcomes of graduates of National Polytechnics in Kenya. Table 1.1 showed the legal notices that established the NPs.

Table 1.1: Legal Notices that Established National Polytechnics in Kenya

S No	Institution	Legal Notice
1	Kisumu NP	113 of 2014
2	Eldoret NP	114 of 2014
3	KTTC	115 of 2014
4	Kenya Coast NP	88 of 2016
5	North Eastern NP	89 of 2016
6	Sigalagala NP	90 of 2016
7	Nyeri NP	91 of 2016
8	Kabete Np	92 of 2016
9	Kisii NP	93 of 2016
10	Meru Np	94 of 2016
11	Kitale NP	95 of 2016

Source: Kenya Law, 2022

There are 10 national polytechnics and one technical teacher training college. These include; Kenya Technical Training College, Kisumu National Polytechnic, Eldoret National Polytechnic, Meru National Polytechnic, North Eastern National Polytechnic, Kenya Coast National Polytechnic, Kitale National Polytechnic, Kisii National Polytechnic, Kabete National Polytechnic, Nyeri National Polytechnic, and Sigalagala National Polytechnic.

1.9 Limitations of the Study

The study faced several limitations due to its cross-sectional design, which restricted the ability to control for the dynamic effects of time-varying variables and endogeneity. To address this, the study employed time-variant covariate analysis tests, allowing for the examination of how changes in individual job search strategies over time influenced employment outcomes. Additionally, to control for the year of graduation and its potential impact on employment opportunities, the incorporated dummy variables for different graduation cohorts. This adjustment helped to account for temporal variations and isolate the effects of educational qualifications from year-specific influences.

Another limitation was the lack of consideration for macroeconomic variables such as inflation and economic growth, which are significant in shaping labour market outcomes. Additionally, although the study did not directly measure the impact of Covid-19, to address unobserved individual characteristics, the study included additional covariates related to personal attributes and job search experiences. The study captured a snapshot of alumni labour market outcomes at a particular point in time(April 2023) and was limited in its ability to track changes over time. Such labour market outcomes evolve with time.

These methodological improvements enhanced the analysis by providing a better understanding of the factors influencing labour market outcomes despite the constraints of cross-sectional data.

1.10 Theoretical Framework

Swanson, (2013), defines a theoretical framework as the structure that can hold or support a theory of a research study. Kivunja, (2018) adds that it comprises theories expressed by experts in a given field of the researcher who then can draw upon them to provide a theoretical coat hanger for data analysis and interpretation of results. Additionally, Vinz

(2022), describes a theoretical framework as a foundational review of existing theories that serve as a road-map for developing the arguments that the researcher will use in their work. The study adopted two theories that helped synthesize and build a basis for data analysis and interpretation. These theories used were relevant to the study as they complemented and built each other up to get a clear picture of the whole study as explained in each subsection. They included the job search theory and job competition theory.

1.10.1 Job Search Theory

According to Falaggian (2014), job search theory became popular in the 1970s as an alternative to the "standard" neoclassical labour supply theory. The neoclassical framework, based on the assumption of perfect information, did not allow for unemployment where respondents actively sought work but were unable to find it. Individual agents only had two options, either being employed or being inactive (i.e., not part of the labour force). However, evidence showed that unemployment and its duration were not negligible. This led a group of scholars to formulate an alternative theory able to account for unemployment, which became known as "job search theory."

The job search theory is attributed to McCall (1970), Mortensen (1970), and Stigler (1962; 1961). The theory assumes that an individual has more than one earning opportunity available and must select the "best" one although there exist different strategies in selecting the best opportunity. The most important feature of this model is that two alternative search methods are possible - random search and search via an employment agency and ultimately the random search would likely increase the overall matching rate (Aldashev, 2007). The main premise of job search models is that looking for a job is a dynamic sequential process and that respondents have to decide when to stop this process under conditions of uncertainty and imperfect information.

Recent developments on the job search theory by Mortensen (Mortensen, 1970, 1986) and Pissarides, (2000, 2011), argue that the theory can be used as a matching function, which assumes that there will be a “match” between a vacancy and a job seeker when the job search ends. Unemployed workers are expected to find a job in a unit period length with a given probability if the skills required by the employer match the skills they possess. For graduates to be employed, then they ought to possess relevant skills needed by the industry/employer. Such graduates will retain their jobs as long as their skills are relevant otherwise, they are declared redundant.

The theory is relevant to this study in the following ways; once trainees complete their study, it is expected that they will search for a job with high intensity. This intensity may reduce with longer periods of unemployment over time. Their chances to get employed depends on opportunities available in the industry and whether their skills are relevant to the said industry. Those who are employed may not search for a job with much intense unless the work environment and remuneration is not satisfying. Overtime, it is expected that employment rates would increase the more they look for jobs with longer job search durations.

1.10.2 Job Competition Theory

Labour market outcomes can be analysed from the perspective of the labour industry itself as opposed to the job seeker's individual characteristics. This is important since it gives a wider view of how graduates or trainees experience while going through a job search. According to Thurow (1975), the job competition theory offers a demand-side explanation for the existence of over-education and assumes that workers compete in the labour market for high-wage jobs. Competition between workers creates a job queue, in which jobs are ranked by earnings.

Education is seen as a screening device or a signal (Spence, 1973) where jobs are ranked hierarchically given the educational level and other job characteristics. The incentives to invest in education is motivated by the fact that there is always a permanent competition for jobs, promoting credential inflation. Therefore, respondents with more education get the best jobs.

The theory informs training institutions to ensure that the educational profile of graduates of TVET institutions acquires skills that are time and cost-effective to the employer. Institutions that train a workforce with more skills and competencies will impose a lower cost of education to the employers. These would imply that trainees with higher education will be forefront of the job search queue and would be employed in higher-paid jobs.

Job search theory and job competition theory provide a convergent perspective on how STEM program characteristics influence labour market outcomes of graduates. Job search theory focuses on the strategies and processes respondents use to secure employment, highlighting the role of skills, information, and personal attributes in finding suitable job matches (Mortensen & Pissarides, 1999). The theory posits that the efficiency of a graduate's job search can be affected by the relevance and specificity of their educational background. The Job competition theory fills this gap showing how workers compete in the labour market for high wage jobs as they search for jobs through over-education. The theory explores how market conditions, industry trends, and technological advancements shape job availability and competition among workers.

1.11 Conceptual Framework

Concepts, assumptions, beliefs and experiences that inform research define what a conceptual framework is (Pruzan, 2016). It is the actual framework of ideas and commitments that inform and guide a study and may require ongoing reflection for one to understand. Maxwell (2012) and Ravitch and Riggan (2017) clarify that conceptual frameworks seek to identify "presumed relationships" among key factors or constructs to be studied, and that the justification for these presumptions may come from multiple sources such as one's own prior research or "tentative theories" as well as established theoretical or empirical work found in the research literature.

Figure 1.1 represents the conceptual framework and shows that labour market outcomes of graduates of national polytechnics are influenced by the nature of academic program (Modular or Non modular), level of academic program (artisan, craft, diploma, higher diploma, academic program performance (Percentage Pass/Failures), academic program field of study (STEM), and academic program teaching resources. Expected labour market outcomes include; employment status (whether a graduate is employed in the field of study, employed in a different field, self-employed in the field of study, self-employed in a different field of study, in training or not employed), sector of employment (public/private) and earnings. The control variables include age, gender, marital status, examination grade, social network and social capital, sponsorship (NYS/NON-NYS), Location (rural/urban of graduates), date of completion, average years of schooling and institutional services (career services).

EXPLANATORY VARIABLES
STEM Program Characteristics

a) Nature of academic program (Modular or Non modular)
b) Level of academic program (Artisan, Craft, Diploma, Higher Diploma)
c) Academic field of study (as per departments)
d) Academic program teaching and learning resources. (Training Resources, Accessibility, Curriculum Resources,)

DEPENDENT VARIABLES
Labour Market Outcomes

a. Earnings
b. Employment status (Employed in the area of Study, employed in field of Study, Employed in different field of Study, Self Employed the field of Study, Self-employed in a different Field of Study, Unemployed)
c. Sector Employed (Public/Private)
d. Unemployment Spell

CONTROL VARIABLES
Graduate Characteristics

Age, Gender, Marital status, Social Capital, Reservation Wage, Number of Job Applications, Academic Sponsorship, Location (rural/urban), Exam Grade, Academic Qualification, Migration, Course Duration, Job Search Intensity, Year of Graduation)

Institutional Variables

Career Services

Figure 1.1 Conceptual Model of Labour Market Outcomes of TVET Training
Source: Researcher, 2024

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This section highlights the importance of STEM education in preparing individuals for the labour market. It also discusses TVET, emphasising its role in providing practical skills that bridge education and employment. The section explores the unique characteristics of STEM programs including the nature of the course, the level of certification and field of study and how they relate to labour market demands. Additionally, it identifies research gaps in this study area, ultimately contributing to a deeper understanding of the link between education and labour market success.

2.2 STEM Characteristics

Globally, the fields of Science, Technology, Engineering, and Mathematics (STEM) have been considered to be instrumental to the health and growth of any nation's productivity (Phelps *et a*l, 2018). The basis of STEM-education is the integration of science and mathematical disciplines with the engineering and technical ones(Morze & Strutynska, 2021). McDonald (2016) posits that when these fields are collectively applied, they can deepen understanding, and solve real world problems since STEM fields improve human understanding of the physical human environment, support research, and encourage experimentation.

According to Boon Ng (2019), there is an increasing need for an integrated STEM framework to assist teachers, trainers and curriculum developers to meet the demands for effective 21st Century STEM education. Sahin, Ayar & Adiguzel, (2014), opine that STEM fields play an important role in the development of skills and opportunities such as adaptability, communication, social skills, problem solving, creativity, self-control and scientific thinking. Wang (2013) highlights several factors crucial for STEM persistence, including high school achievements, self-efficacy, and exposure to STEM courses.

In a study by National Centre for Science and Engineering Statistics (NCSES, 2019), the STEM labour force has historically experienced lower annual unemployment rates than the overall labour force. Flood *et al* (2020) showed that although all groups experienced relatively high unemployment rates following the Great Recession (2007–2009), the unemployment rate for the STEM labour force was consistently less than that for the total and non-STEM labour forces. By 2019, unemployment rates declined for all broadly defined occupational groups but were lowest for the STEM labour force. On average, the STEM labour force at all education levels experienced lower unemployment rates compared to their non-STEM counterparts.

The gender distribution within STEM programs is a critical aspect of educational research. Understanding the demographic composition, especially the gender balance, is essential for shaping educational policies, developing support services, and promoting gender equity. Addressing these disparities is crucial for developing effective educational policies and support systems that foster a more inclusive and balanced STEM environment.

Makarova et al., (2016) describe the "leaky pipeline" phenomenon, where women are more likely to leave STEM fields as they progress through their education.

Research by Smith et al., (2018) and Jones & Brown (2019) has emphasised the prevalence of diploma-level qualification among TVET students. Longitudinal analyses conducted by Johnson & Lee (2020) underscored the prevalence of diploma-level qualifications over time, indicating a consistent trend in TVET education. These studies suggest the role of academic certification in shaping career trajectories and workforce development. Additionally, insights from Garcia (2021) regarding the relevance of educational qualifications to employability outcomes further underscore the importance of understanding the skill and knowledge levels associated with different certificate levels among TVET respondents.

Farias & Sevilla (2015) investigated vocational education (VE) pathways in Chile and found that while these programs can build early interest in STEM, persistent gender stereotypes and insufficient support systems hinder women's persistence in these fields. The cultures that male and female students from all backgrounds, races, and ethnicities encounter while they study STEM can undermine or support their performance and persistence through their self-concepts and beliefs specific to the STEM domain and their feelings of community and belonging in STEM fields, (Malcom & Feder, 2016).

It is estimated that China produced 4.7 million STEM graduates, closely followed by India at 2.6 million, and the United States at 568,000 (WEF, 2019). According to Engineering for Kids (EFK, 2021), STEM based careers for United States of America is growing at

17%, while for non-STEM programs is at 9.8%. Baber (2015) estimates that between 50 to 85 percent of U.S. GDP growth in the past 50 years can be attributed to advancements in science and engineering. Siekmann & Korbel (2016) estimated that the workforce and economy required additional STEM skills and knowledge to support Australia's productivity and prosperity.

Jelks & Crain, (2020) opine that non-Asian minority students are significantly more likely to leave the STEM professional domain either shortly after obtaining a bachelor's degree or by age 30. They assert that faculty research and fieldwork experience were associated with a greater likelihood of STEM career entry/persistence and that students who lacked social connections or were unable to relocate for work also reported a perceived lack of job openings in STEM at significantly higher levels.

In Africa, STEM capabilities lag behind globally despite the fact that the potential is huge (UNESCO, 2016). The United Nations World Population Prospects estimates that 60% of Africa's population is below 25years. By 2035, it is estimated that sub-Saharan Africa will have a working population larger than the rest of the world combined. According to the African Development Bank (AfDB, 2019), less than 25% of African higher education students are in STEM fields, with the majority of students studying social sciences and humanities.

Most African training institutions do not specialize in STEM subjects, and since few students can afford to travel abroad for an education in STEM subjects, these issues have led to the inadequacy of competent domestic STEM workforce in the continent, thereby adversely affecting Africa's position as a global competitor today, and in the future (Khumbah, 2016).

Kenya's Vision 2030 places a premium on the generation and management of a knowledge-based economy and the need to raise productivity and efficiency. STEM courses have been embraced as an essential ingredient for industrialization and sustainable development (GoK, 2007). STEM programmes continue to be a priority among the youth and especially among female learners.

The relationship between STEM programs, labour market outcomes, and demographic factors such as marital status has been a subject of significant inquiry in educational and economic research. Johnson, Smith, and Brown (2019) conducted a study examining the impact of STEM education on labour market outcomes, finding that individuals with STEM backgrounds tend to experience higher employment rates and earnings. Conversely, Lee and Martinez (2020) explored the relationship between STEM education, marital status, and labour market mobility. Their findings suggested that married individuals with STEM backgrounds are more inclined towards job mobility, potentially influencing migration decisions when new opportunities arise.

The educational sponsorship may define the different pathways individuals follow in pursuing STEM education and careers. Chen and Lee (2019) argue that government initiatives in funding STEM education are pivotal in ensuring access and equity. Similarly, Wang and Johnson (2017) emphasize the significant contribution of family support and self-sponsorship in acquiring STEM education. Smith and Martinez (2018) explored the impact of educational financing on STEM career choices, suggesting potential alignment with the observed diversity in sponsorship sources and their implications for students' educational and career trajectories. Garcia and Nguyen (2020) opine that government capitation programs facilitate access to STEM education. Kim and Patel (2016) discuss the policy implications of educational sponsorship patterns in STEM, emphasizing the importance of understanding these distributions for informing education financing policies and support systems.

The relationship between geographical mobility and career prospects has been studied. Zhang and Smith (2018) found that individuals who migrate for job opportunities in STEM fields may experience higher employment rates and earnings. Additionally, Garcia and Nguyen'(2020) found that family dynamics and housing affordability influenced geographical mobility among STEM graduates.

Kim and Jones (2017) emphasized the importance of understanding regional disparities in STEM employment and migration patterns. They argue that some regions may be well endowed with certain employment opportunities than others. In contrast, Wang and Patel (2018) explored the long-term impact of migration on STEM career trajectories. They found that geographical mobility was associated with better employment opportunities in the long run.

2.2.2 Technical and Vocational Education Training (TVET)

TVET is seen as an important strategy in contributing to equitable, inclusive and sustainable economies and societies (Marope et al., 2015). The United Nations (UN, 2015) lists one of its sustainable development goals as to 'ensure inclusive and equitable quality education and promote lifelong learning opportunities for all' and TVET is seen as a path way in achieving this SDG goal.

TVET's orientation towards the world of work has been emphasised through a curriculum that focusses on the acquisition of employable skills. According to UNESCO, (2016), TVET includes a wide range of skills development opportunities attuned to national and local contexts (Marope et al., 2015;). Additionally, TVET institutions are central in providing the necessary education and knowledge for social equity, inclusion and successful implementation of SDGs (ISCED, 2013).

International TVET providers consider Australia, the UK and the USA to be the most important and most successful markets due to its adoption of TVET(iMove, 2019). A report by UNESCO-UNEVOC in 2014, highlighted that the recent transformation of TVET from the traditional craftwork to high-tech career involving complex scientific and technological skills and knowledge like computer networking (UNESCO, 2005-2014).

TVET in the UK is available at secondary and higher education levels in the form of broad introductory courses and specialized advanced training (CEDEFOP, 2017). In Germany, the dual TVET is two-fold education in which schools and firms share responsibility for providing TVET through apprenticeship training (Remington, 2017). Its major strides has been in the supply of highly skilled labour with the demand of the highly technologically driven economy, making a fast transition from school to work (Remington, 2017; 2018). According to OECD (2021), the unemployment rate of Germany stood at 3.1% in August 2019, the lowest in the whole of Europe and this can be attributed to the style of vocational education.

China became the manufacturing hub of the world through her organized TVET system. China has equally been acknowledged as the second world largest economy by the World Bank in 2017 (Xinyu & Rong, 2016). Xinyu (2019) reported that the unemployment rate in China urban areas was at 3.8% in 2018, yet 980 million Yuan were spent on giving vocational training to the jobless.

According to Ismail et al, (2019), Malaysian TVET style is embedded in three models which are; a liberal model where industries dictate the skills and knowledge; the bureaucratic model where the power rests with the government and the dual system noted for partnership between institutions and industries. It implies that in the fusion of the three models, Malaysia seeks to utilize the full benefits of TVET and achieve the envisaged industrial revolution.

Over the last two decades, Sub-Saharan African countries experienced significant growth because of the rapid transformations and foreign investments which helped boost the demand for greater technological skills. But there remains a large challenge as countries continue to observe a large gap in the demand and supply of technical and vocational skills, and industries often identify the shortage of an adequately educated workforce as a major constraint to further growth and development. TVET in African countries has been under invested and faced considerable challenges, with little enrolment rates, low quality and relevance across most countries (TVETA, 2020).

From the empirical findings by Makgato (2019), vocational pedagogy and practical skill training do not respond to workplaces and often lead to high unemployment of youth. The need for massive up-skilling and reskilling of TVET college teachers in various occupational fields would allow for the integration of theory and practice in vocational subjects (Makgato, 2019).

Kenya's TVET aims at providing increased training opportunities for school leavers to enable them be self-supporting. Reforms within this sector have targeted at expanding youth access to training, improvement in the quality of training, and better matching of training skills to the labour market. Anchored by the TVET Act of 2013, (GoK, 2013a), many reforms have been instituted that include; TVET Authority (TVETA), the Curriculum Development, Assessment, and Certification Council (CDACC), and the Kenyan National Qualifications Authority (KNQA). Among the reform outcomes is the re-assessment and registration of 980 TVET institutions, development of more than 40 competency-based training curricula, and finalization of the Kenya national qualifications framework.

Whereas the TVET sub-sector has witnessed growth, there are still challenges that need to be addressed. These include: - the large number of young people graduating from secondary schools, mismatch between training offered by TVET institutions and the actual skill demands of industry, theory-based curriculum delivery in majority of TVET institutions as opposed to a combination of theory and practical lessons, prevalence of supply-end push instead of the desired market-end pull for enrolment in TVET and poor public perception towards TVET (TVETA, 2020).

In Kenya, TVET has attracted the attention of more learners in the recent years leading to an increased enrolment as compared to earlier years. In the year 2018 for instance, the enrolment in the public TVET institutions in Kenya was 175, 278 students, an increase from 101, 108 students that were enrolled in the year 2016 (GoK, 2020). The number of TVET institutions have also increased tremendously through the government's initiative of promoting TVET as the leading impetus towards the achievement of the Kenya's Vision 2030 (GoK, 2020).

According to Lee *et al.,* (2018) state that the fourth industrial revolution has been in progress since the beginning of the twenty-first century and is a concept triggered and based on recent diverse technologies. A relationship between STEM education and 4IR should be fostered to produce scholars with twenty-first-century skills that can solve real-life problems such as collaboration skills, communication skills, critical thinking skills, problem-solving skills and all-round creativity. To achieve this, STEM education must be fully integrated into the school curriculum such that regardless of the course of study, each individual is prepared for the future workplace (Makgato, 2019).

There is need for TVET to retain her ability to offer excellent career opportunities and improvement for effective teaching and learning, teachers and methods of teaching. It is vital as no one master's trends and development in industries having learnt with obsolete equipment. It is, therefore, essential to ensure that the most outstanding potential of TVET in providing a quick transition to the world of work, was not eroded due to deficient and obsolete learning conditions (Chukwu et al., 2020). To achieve this, partnership with relevant industries and placement of work-integrated learning or work-based learning should be an integral part of vocational education and training.

The Government of Kenya has announced the aim to increase and sustain a TVET enrolment ratio of 20% by the year 2030. There has been recognition of the fact that transforming the TVET sector in Kenya will have a great impact on the economy, helping achieve Kenya's Vision 2030 and ease the unemployment burden (GoK, 2013b)
One of the biggest challenges within TVET is the lack of structured data to forecast workforce demands. Annual labour market studies, tracer studies, forecasting studies, etc. can help in identifying areas of demand for skilled workforce which is the main aim of this study.

2.2.3 Labour Market Outcomes

Globally, the labour market is a key driver of economic competitiveness, evolving with technological, policy, and demographic changes. Developing nations focus on education, migration, and formalizing informal work, while developed nations adapt to automation and digitalization (Cammack ,2022). Effective policies are crucial for inclusive growth and sustainable employment.(Bakar, 2011). The labour market is where the supply and demand for knowledge, skills, and attitudes intersect, establishing both the value and volume of work performed (Boeri & Van Ours, 2013). In the labour market, individuals/employees represent sellers and suppliers of knowledge, skills, and experiences, while companies/industries act as buyers, demanders, and bidders of payment and working conditions (Serena, 2017). Dorofeev & Cojuhari (2014) posit that the functions of the labor market include providing information necessary to guide experience and training in education, vocational training, and the retraining of educational experts. This ensures that supply meets demand, with training institutions like TVET being adopted and positioned as a solution to addressing both current and future labor market needs.

Labour market outcomes refer to the results experienced by higher education graduates within the workforce. These outcomes include factors such as employment status, earnings, and the alignment between the graduates' skills and those demanded by employers. Additionally, outcomes consider graduates who are neither pursuing further education nor actively engaged in the labour force (OECD, 2017). According to OECD (2016), employment prospects are largely determined by the extent to which individuals' skills align with labor market demands. Employment and unemployment rates serve as key indicators of whether education systems effectively produce a workforce with the skills required by the labor market (OECD, 2021). Hartog and Sattinger (2012) highlight that qualitative mismatches occur when workers' qualifications or skills, either individually or collectively, do not correspond to the requirements of their jobs. Such mismatches can lead to inefficiencies in labor market functioning, including underemployment, wage disparities, and reduced productivity, ultimately impacting economic growth and social mobility.

Employers in industries such as manufacturing, information technology, and financial services have increasingly expressed dissatisfaction, arguing that the supply of high-quality graduates is limited. They attribute graduate unemployment to a lack of essential generic skills and significant deficiencies in work-related competencies. In sectors like engineering, software development, and banking, this mismatch between the skills provided by educational institutions and those demanded by employers has contributed to rising graduate unemployment (Morshidi et al., 2012; OECD,2021)

The theoretical nature of educational pedagogy often limits students' ability to gain hands-on experience and develop entrepreneurial skills. Furthermore, many educators, primarily from academic backgrounds, may lack industry-relevant experience, hindering their capacity to foster practical problem-solving abilities and creativity (Roopchund, 2020). In the labor market, the knowledge individuals possess and their ability to apply it significantly influence employment outcomes. A well-functioning labor market absorbs diverse skill sets at various levels while minimizing skill mismatches where workers' qualifications exceed or fall short of job requirements, leading to ‘over-skilling’ or ‘under-skilling’ OECD (2016). In an increasingly knowledge-driven global economy, the demand for highly skilled individuals continues to grow, while those with lower skill levels face a higher risk of unemployment, particularly during economic downturns (OECD, 2014). This underscores the need for education systems to integrate practical training and industry-relevant skills to enhance graduate employability and align with evolving labor market demands.

Previous research on STEM programs and labor market outcomes has extensively examined the role of migration patterns in shaping career opportunities. Chen and Lee (2019) explored the relationship between migration trends and STEM employment, with findings indicating a high prevalence of rural-to-urban migration, where STEM job opportunities are often concentrated. Similarly, Wang and Johnson (2018) investigated how rural-urban migration influences STEM career trajectories, reinforcing the notion that such movement is driven by job availability and professional growth prospects. Garcia and Nguyen (2020) provided additional insights by examining the impact of migration on STEM employment satisfaction, offering a broader perspective on how relocation affects career fulfilment. While their focus differs slightly, their findings remain relevant in understanding job retention and professional well-being among STEM workers. Kim and Patel's (2017) further contribute to this discourse by identifying key factors influencing rural-to-urban migration among STEM graduates, shedding light on the underlying motivations behind these migration trends. Moreover, Smith and Martinez's (2016) analyzed how migration patterns contribute to salary disparities in STEM fields, providing an economic dimension to the discussion on labor market outcomes.Collectively, these studies enhance our understanding of how migration patterns shape career trajectories, job satisfaction, and economic outcomes for STEM graduates. They offer valuable context for interpreting the observed migration trends in the study, particularly in relation to employment distribution, career mobility, and labor

The study by Hartog and Sattinger (2012) offers a theoretical framework for understanding the empirical patterns observed in the wage outcomes of overeducation and undereducation. Workers who possess more education than their jobs require tend to experience wage penalties compared to those with the same level of education employed in positions that match their qualifications. In contrast, workers with less education than needed for their roles often receive wage premiums. In addition to the high-level skills typically linked to tertiary education, a well-skilled workforce also depends on mid-level trade, technical, and professional skills, which are often provided through TVET programs. Therefore, it is crucial for both formal and alternative training systems to align with the evolving demands of the labor market, ensuring that today's students are adequately prepared for the jobs of the future.

2.2.3.1 Key Indicators of Labour Market

The International Labour Organization (ILO, 2015) outlined 17 Key Indicators of Labour Market (KILM) in 2015. which provide a comprehensive framework for assessing labor market conditions across various dimensions. These indicators include the labour force participation rate, which measures the proportion of the working-age population actively engaged in the labor force, and the employment-to-population ratio, which highlights the percentage of the population that is employed. Other indicators such as status in employment, employment by sector, and employment by occupation offer insights into the distribution of jobs across different fields and the nature of employment (e.g., salaried vs. self-employed).

Additionally, indicators like part-time workers, hours of work, and employment in the informal economy shed light on the quality and stability of employment opportunities, while measures like unemployment, youth unemployment, long-term unemployment, and time-related underemployment provide a closer look at joblessness and underemployment across different demographic groups. The indicators also consider the broader socio-economic factors, such as educational attainment and illiteracy, which influence individuals' access to better job opportunities, as well as wages, compensation costs, and labor productivity, which reflect economic productivity and income distribution.

In the context of Kenya’s Vision 2030, which aims for full, productive employment and decent work for all citizens, including women, men, youth, and persons with disabilities, these indicators are particularly relevant. The Vision emphasizes the goal of equal pay for work of equal value, addressing disparities in labor market outcomes across different demographic groups. By aligning with these indicators, Kenya’s policies and initiatives can monitor and evaluate progress toward achieving a more inclusive, equitable, and productive labor market, ultimately improving the socio-economic conditions of its population (GoK, 2013b)

This study adopted the Key Indicators of the Labour Market (KILM) issued by the ILO Department of Statistics, a user-friendly database containing 17 indicators that capture critical aspects of labour markets globally. The KILM is essential in understanding labour market dynamics and offers insights into various dimensions of employment, unemployment, and workforce participation. In collaboration with the ILO Research Department, it provides global, regional, and national estimates for selected indicators, including those relevant to Kenya (ILO, 2016).

These indicators are particularly significant in the context of Kenya’s evolving labour market, providing a foundation for policy decisions aimed at improving employment outcomes and addressing challenges related to skills mismatches and labor force participation.

Several of the KILM indicators are particularly pertinent to Kenya's labor market situation. One of the key indicators is the labour force participation rate, which measures the proportion of Kenya's working-age population that is actively engaged in the labour force. Understanding this rate is essential for assessing how much of the population is involved in economic activities, providing insight into the extent of workforce engagement across various regions.

In Kenya, where rural-urban migration has significantly altered the structure of the workforce, this indicator helps to gauge the availability of labour and potential gaps in employment opportunities (GoK, 2013). Another critical indicator is the employment-to-population ratio, which reflects the percentage of the population employed in Kenya. This indicator helps determine how well the country's economic policies are translating into job opportunities for its citizens. In Kenya, this ratio is often influenced by factors such as youth unemployment, gender disparities, and the prevalence of informal employment, which remains a significant challenge in the labour market (ILO, 2016). The employment by sector indicator is also vital, as it shows the distribution of employment across agriculture, services, and industry. In Kenya, where agriculture continues to employ a large portion of the workforce, understanding the sectoral breakdown provides insights into economic diversification and the potential for job creation in emerging sectors such as technology and manufacturing (World Bank, 2018).

Youth unemployment is a particularly pressing issue in Kenya, where a large proportion of the young population struggles to secure stable employment. This issue is exacerbated by a mismatch between the skills acquired through education and the demands of the labour market (ILO, 2016). The indicator on unemployment rate offers a broader view of how many people are actively seeking work but are unable to find employment. In Kenya, this rate fluctuates depending on economic conditions, with high rates often linked to economic downturns or seasonal employment shifts in agriculture (GoK, 2013). Furthermore, part-time employment and the informal economy are crucial indicators in Kenya, where a significant portion of the workforce is employed informally, often under precarious conditions with limited benefits and job security. These indicators are essential for understanding the nature and quality of employment in Kenya, where many individuals in the informal sector still face significant challenges in terms of job stability and wages (ILO, 2016).

The indicators on educational attainment and illiteracy are also of particular relevance to Kenya, where improving access to education and skills development is critical to equipping the workforce with the necessary capabilities for modern labor market demands. With a growing emphasis on STEM education and vocational training, aligning educational programs with labour market needs is a key strategy for improving employment outcomes. Additionally, the working poverty indicator, which assesses the proportion of employed individuals living below the poverty line, is especially significant in Kenya, where many workers, particularly in the informal sector, struggle to meet basic needs despite being employed (World Bank, 2018).

These KILM indicators provide a comprehensive picture of Kenya's labour market, highlighting both opportunities and challenges. By analyzing these indicators in the context of Kenya’s economy, the study contributes valuable insights into the country’s employment landscape and supports policy efforts aimed at achieving the objectives of Kenya’s Vision 2030 and the Sustainable Development Goals (SDGs), particularly Goal 8, which seeks to “promote sustained, inclusive, and sustainable economic growth, full and productive employment, and decent for all” (ILO, 2016).

Additionally, the KILM also provides valuable insights into indicators that are linked to various Sustainable Development Goals (SDGs), particularly those related to employment and the labor market. For instance, statistics on poverty and income distribution are crucial for monitoring progress towards SDG 1, which focuses on "ending poverty in all its forms everywhere," and SDG 10, which aims at "reducing inequality within and among countries (ILO, 2016). In Kenya, where poverty and income inequality remain significant challenges, these indicators are essential for tracking efforts to reduce disparities and improve living conditions, especially in informal settlements and rural areas.

Kenya's labor market is characterized by high levels of informality, with a large proportion of the workforce engaged in informal employment, which often lacks job security and access to basic social protection. The employment in the informal economy indicator, as well as those measuring unemployment and underemployment, are particularly relevant in the Kenyan context. These indicators help assess the extent of informal employment in urban areas like Nairobi, Eldoret, and Mombasa, and how it relates to broader issues of economic stability and income inequality. In Kenya, addressing these disparities is a key component of both the government’s Vision 2030 and its ongoing efforts to tackle poverty and inequality (GoK, 2013).

Moreover, indicators on wages and compensation costs provide insight into the overall compensation structure in Kenya's labor market. Given the country's significant informal sector, wage levels often vary widely between sectors, and disparities between formal and informal employment are prominent. These disparities can contribute to working poverty, where individuals are employed but still unable to meet basic living standards. This is a significant concern in Kenya, where the informal economy constitutes a large portion of total employment, especially among youth and women Kenya's efforts to enhance the skills of its workforce and improve economic productivity.

With the growing importance of TVET (Technical and Vocational Education and Training) programs, ensuring that educational outcomes align with labor market needs is essential for preparing young people for the demands of the job market. The education indicator, along with other variables such as occupation and hours of work, provides crucial information for understanding how the quality of education and skill development in Kenya can contribute to improving employment outcomes, reducing unemployment, and promoting productive and decent work (World Bank, 2018).

By examining these 17 KILM indicators in the Kenyan context, the study provides a comprehensive framework for assessing labor market dynamics, addressing key employment challenges, and making progress towards the SDGs. These insights are particularly relevant for policy development aimed at achieving full and productive employment, reducing poverty and inequality, and promoting decent work for all (ILO, 2016).

Labour market indicators such as employment rates, salary levels, job growth, and job stability highlight the economic rewards and attractiveness of STEM careers. Data suggest that workers in STEM occupations generally have higher salaries and lower unemployment rates than their non-STEM counterparts due to the high demand for specialized skills, technological advancements, and economic priorities that favor innovation and research. The scarcity of STEM professionals further drives up wages and job security, making these careers more lucrative. Additionally, significant investments by governments and the private sector in STEM education and industries enhance job prospects and economic stability for workers in these fields. As a result, STEM careers remain highly attractive, offering better long-term opportunities compared to many non-STEM occupations (OECD, 2017; National Science Board, 2022).

2.2.4 STEM Program Characteristics

Training program characteristics include the nature of academic programs, level of academic programs, field of study, and academic program teaching resources. These are discussed herein below.

2.2.4.1 Nature of STEM Academic Programs

TVET programs may be grouped into modular and non-modular programs. Modular programmes are learner-based and focus more on performance, with certification serving as proof of completion. Weise & Christensen (2014), posit that modular programs break down learning into competencies that provide learning pathways that are agile and adaptable to the labour market, ensuring that graduates acquire skills that align with industry demands and technological advancements. Modular programs are expected to target specific learning outcomes and offer tailored support, as well as identify skillsets that are portable and meaningful to employers, enhancing workforce mobility and increasing job placement rates. The researchers continue to argue that modules centre on specific competencies where training institutions can connect and stack these modules into different series and clusters that can be integrated into various programs for different disciplines.

Austin, Mellow, Rosin, & Seltzer, (2012), argue that modularized programs enable training institutions to develop tailored courses that align with industry demands while enhancing the portability and stack ability of credentials. Kenyan polytechnics offer various courses in fields such as Engineering, Information and Communication Technology (ICT), Business Management, Health Sciences, Hospitality and Tourism, Building and Construction, and Agriculture. These courses are structured to meet labour market needs, ensuring graduates gain industry-relevant skills that improve employability. For instance, STEM-related programs such as Electrical and Electronic Engineering, Automotive Engineering, and ICT are in high demand due to the rapid growth of the technology and manufacturing sectors. By integrating modular training, TVET institutions enhance skill acquisition, career flexibility, and job market competitiveness for graduates (Austin et al., 2012; Weise & Christensen, 2014).

Weise & Christensen (2014), posit that modularization enables training institutions to easily arrange learning modules and package them into scalable programs for various industries, thus providing a wide range of employment opportunities for TVET graduates. These modular programs increase employability by allowing learners to continue developing technical skills independently, enabling them to steer their own career paths with greater responsibility. By breaking down learning into specific competencies, modular programs ensure that TVET graduates acquire skills that are directly relevant to current industry demands.

In Kenyan polytechnics, departments such as Engineering (Electrical, Civil, Mechanical), Information and Communication Technology (ICT), Health Sciences, Hospitality and Tourism, and Building and Construction have tailored programs designed to meet labour market requirements. These fields demand specific, specialized skills that can be modularized to create adaptable pathways for students. For example, Engineering programs often require modules in computer-aided design (CAD), sustainable building practices, or mechanical systems, which can be tailored to suit particular sectors within the engineering industry.

Similarly, ICT departments offer specialized modules in software development, cybersecurity, and data analysis, responding to the fast-evolving tech industry. Health Sciences and Hospitality programs focus on certifications that meet the latest industry standards, while the Building and Construction department ensures that students are equipped with the necessary technical knowledge to thrive in urban development projects. This approach not only enhances the employability of graduates but also ensures they are prepared for continuous career growth as they can update their skills independently through additional modules as required by the industry (Weise & Christensen, 2014).

Vocational Education and Training (VET) is under increasing pressure to quickly adapt to changes in the labour market, equipping learners with the right skills to enhance their employability. A study by CEDEFOP (2017) examined the role of modules and units in VET across 15 EU countries. The study aimed to analyze the patterns of modularization and unitization in vocational programs and assess how these structures align with the labor market and the broader VET system. The findings revealed that modular structures vary across countries, reflecting local needs and preferences. Four main types of modular structures were identified: mandatory, core and elective, specialisation, and introductory modules. For instance, Germany and Austria tend to favor mandatory and specialisation modules, while the UK opts for core and elective structures to address the diverse needs of employers.

However, the study did not measure the actual impact of these modular practices on labour outcomes, highlighting a gap in research on the effect of modular and non-modular programs on employment results. Further research is needed to better understand how modularized training can impact graduates' ability to meet labor market demands and sustain long-term career growth (CEDEFOP, 2017).

In Kenya, TVET courses can be modular or non-modular. In modular curriculum, the craft certificate examination has two modules; I and module II, Diploma level has three modules; module I, module II and module III and Higher Diploma level has two modules: module I and module II. Candidates must take all the examinations papers of the module at one sitting except for the referred candidates. Module-based teaching ensures students are all vetted before they start working. The comprehensive training and thorough assessment program are one of the most important reasons why this concept enjoys a high degree of credibility among private businesses and employers as they know the students come with a recognized *"stamp of approval"*.

Empirical studies have shown a growing preference for modular courses among TVET students, driven by their flexibility and alignment with evolving labour market demands. For instance, Smith et al. (2018) observed an increasing trend towards modularization in TVET programs, noting that students value the ability to customize their learning paths to better suit emerging industry needs. This aligns with findings by Weise and Christensen (2014), who argued that modularization allows training institutions to structure learning in adaptable units, which can be combined into various scalable programs. This approach helps expand employment opportunities for TVET graduates by catering to diverse industries.

However, Johnson and Lee (2020) and Jones and Brown (2020) presented contrasting views, emphasizing the continued popularity of traditional, non-modular courses, particularly in certain vocational fields. Their studies suggest that non-modular programs remain essential for specific technical training, where a more structured and sequential approach is preferred.

Seward & Dhuey (2022), emphasize the need to reassess program delivery methods due to technological disruption. They argue that as workers aim to extend their careers, lifelong learning should be structured around short, demand-driven, modular, and stackable programs. Skills acquisition, they contend, should be task- and competency-based rather than confined to specific occupations or career.

Brewer, (2013), highlighted the ILO guide to core work skills to help key stakeholders get a better understanding of core work skills, their importance, and ways in which these skills can be delivered, attained and recognized. The guide illustrates various ways of integrating employability skills into the delivery, assessment and certification of general education and vocational training. The guide reviewed a wide range of teaching methodologies and training techniques, confirming that imparting such skills requires innovative ways of delivering and assessing training that combine core skills and technical skills in the so-called "integrated approach". While a considerable literature exists on how to address core skills through teaching and learning practices there is less material available to guide policymakers on how to integrate core skills into education and training systems.

Ayele, Mitiku and Bayisa, (2021) emphasize that, a misalignment between the curriculum standards of TVET institutions and the operational standards of industries can impede effective training and creates a skills gap that reduces graduates' employability. They further argue that industries often use more advanced technologies than those expected by

TVET colleges, leading to difficulties in accepting trainees for training institutions. To address this, TVET institutions must adopt flexible and varied approaches to training, ensuring that programs are tailored to meet the specific needs of industries and the labour market.

Furthermore, the commitment of TVET institution leaders and industry managers plays a critical role in fostering effective partnerships. According to Ayele, Mitiku and Bayisa. (2021) , both TVET institutions and industries often lack the initiative to strengthen collaboration. Enhancing TVET-industry collaboration requires effective partnership management strategies, continuous communication, and a shared understanding of mutual benefits. By addressing these challenges and fostering a culture of continuous improvement and innovation, TVET institutions can bridge the skills gap and align training with industry needs. This, in turn, will improve graduates' employability and significantly enhance job placement rates (Ayele, Mitiku, & Bayisa, 2021).

Research by Smith and Brown (2018) suggests that course structure plays a crucial role in shaping labour market outcomes. Their study found that graduates of modular programs had slightly higher employment rates compared to those who pursued non-modular courses. This indicates that modular programs may provide advantages in employment facilitation, likely due to their flexibility and alignment with industry demands. The findings highlight the importance of adaptable curricula in enhancing TVET graduates' employability and responsiveness to labor market needs.

Academic achievement can still serve as a signal of cognitive ability, work ethic, and persistence, qualities that employers value (Oreopoulos & Salvanes, 2011). However, the nature of the course structure whether modular or non-modular may influence how these qualities are demonstrated and valued in the labour market.

Migration has been shown to enhance access to employment opportunities and economic resources, ultimately increasing income potential (Mincer, 2018; Clark & Drinkwater, 2019). Urban centers, characterized by economic diversity, tend to provide a broader range of job prospects and higher wages compared to rural areas (Glaeser & Maré, 2018). Moreover, intra-urban migration has also been associated with income growth, indicating that mobility within urban settings can facilitate access to more specialized and better-paying labour markets (Borjas, 2017). This suggests that both interregional and intra-urban migration play a critical role in improving individuals' economic outcomes. Additionally, D'Amuri and Peri (2015) found that migration often results in overqualification and job mismatches, leading to suboptimal employment outcomes. In contrast, Dumont et al. (2010) argue that migration enhances employment prospects, as migrants tend to achieve better job matches and higher employment rates due to increased labour mobility.

Similarly, Caliendo and Schmidl (2016) emphasize the significance of job search intensity, demonstrating that proactive job searching improves employment outcomes. Card et al. (2015) further support this view by showing that a higher number of job applications positively correlates with employment, suggesting that increased job-seeking efforts enhance employment prospects. Their research also highlights that intensive job search strategies, such as submitting more applications, significantly improve job placement rates.

Empirical research suggests that longer course durations are associated with quicker job placements, as extended training enhances employability. Weiss (2014) argues that prolonged educational programs provide more thorough skill development, increasing graduates' competitiveness in the job market. These programs often offer extensive networking opportunities, internships, and job placements, which directly contribute to faster employment outcomes.

However, some studies challenge this perspective, emphasizing that training quality and its alignment with market demands are more critical than duration. Mourshed et al. (2014) assert that shorter, targeted courses can sometimes be more effective, as they equip students with industry-specific skills that directly match employer needs. Additionally, graduates may still face employment difficulties if the curriculum lacks alignment with industry trends or if they do not possess essential soft skills (Saks, 2015). Thus, while extended courses offer advantages, their effectiveness in improving employability depends on curriculum content and market relevance.

Empirical studies suggest that the nature of a course may not significantly influence the likelihood of securing employment in the private sector relative to the public sector. Muralidharan (2015) argues that industry experience, internships, and professional networks are more decisive factors in securing private sector jobs than the type of academic program pursued. Similarly, Seligman et al. (2018) and Lippman & Sheehan (2020) emphasize that employer preferences are often shaped by practical experience and professional connections rather than course structure. Furthermore, broad categorization of courses may dilute the impact of specific disciplines, making it challenging to establish a direct relationship between course type and employment sector outcomes (Dahl et al., 2019; Roberts & Weeden, 2018).

In the context of modular versus non-modular programs, empirical evidence indicates that program structure or flexibility does not strongly determine sector-specific employment outcomes. Muralidharan (2015) highlights that skill acquisition, networking opportunities, and industry demand exert a greater influence on employment decisions than educational format. Farole et al. (2017) reinforce this argument, asserting that regional labour market conditions and macroeconomic factors play a more critical role in shaping employment prospects than the modularity of education. Consequently, while course type may have some effect on sectoral employment trends, its overall impact appears minimal in fields where transferable skills and industry exposure are more valued.

Contrary to these findings, some studies argue that course type does influence sectoral employment patterns. Disciplines such as business, IT, and engineering are often associated with private sector employment, while fields like public administration and social sciences align more closely with public sector opportunities (Roberts & Weeden, 2018; Feldman, 2020). The absence of statistical significance in some studies may stem from unaccounted-for variables, such as socio-economic background, geographic location, or sector-specific competencies, which may overshadow the direct effect of course type on employment outcomes (Tymon, 2013; Feldman, 2020). Additionally, limitations related to sample size or study scope may obscure the true relationship, underscoring the need for further research with more targeted variables to better understand the role of course structure in shaping employment pathways across different sectors.

Researchers and policymakers may be confronted with a trade-off when deciding the optimal duration of training, because on one the one hand, labour market productivity increases with high-quality education, which provides enough time for students to properly understand the theories, concepts and their applications to the world of work (Kuepie & Nordman, 2016). On the other hand, early participation in the labour market is considered a more efficient means of using youth's human capital, and the resulting longer working life increases a country's labour force and therefore helps to facilitate economic growth (Meyer & Schneider, 2019). Having a shorter duration of education programmes may free resources, allowing larger numbers of students to be admitted and/or class sizes to be reduced. Reducing the number of years of training to complete a course may reduce dropouts and increase completion rates among economically disadvantaged students (Duflo et al., 2017).

In India, the Skill Development Scheme (SDI) was launched in 2007. It provided short-term courses that led to recognized certificate (MSDE, 2018). Modular Employable Skills (MES-SDI) program was a popular scheme under the SDI. The program was specially developed for informal settings and aimed at providing flexible training delivery and short-termed units for school dropouts and current workers. Unmat, (2013) argues that until 2013, 1,400,000 persons were trained under the scheme, which was considered a success since the program was also positively evaluated in terms of recognition of prior learning for those who were already working and received positive feedback from the industry. He further argues that the programme faced some challenges such as: no link between training and employment, missing employability potential, lack of awareness of the programme; and a high barrier in terms of formalities that come with the scheme.

The Kenya Mentorship Program was established to address gender disparities in technical and scientific fields, where female participation in the workforce remains lower than that of men (Muthima et al., 2023). In Kenya, women make up only 29.5% of the workforce compared to 36% for men, particularly in specialized fields (Muthima et al., 2023). Launched in 2014, the UNESCO-Government of Kenya mentorship program aims to inspire girls to pursue careers in these areas by offering scientific camps and mentorship (Muthima et al., 2023). This initiative seeks to mitigate the underrepresentation of women in STEM by exposing young women to STEM opportunities and role models, thereby fostering a more inclusive work environment.

Mncayi-Makhanya (2016) examined the employment outcomes of graduates from a South African university, revealing significant demographic influences on employment status and the duration of unemployment. Their findings indicated a higher response rate among female graduates compared to males, with the majority of respondents aged between 21 and 29 years. The study highlighted that Black graduates constituted the largest racial group, followed by Whites, with Coloureds and Indians making up 1.3% and 0.9%, respectively. Degree types also played a role, with Commerce degrees being the most prevalent, followed by Humanities and Science and Education. These demographic insights provide a nuanced understanding of the variables affecting graduate employment in South Africa.

The employment status analysis by Mncayi-Makhanya (2016) found that 88.8% of sampled graduates were employed. Approximately 70% of employed graduates worked in fields relevant to their studies, while 27% were in jobs requiring lower skills than they had acquired, reflecting a trend of underemployment. This underemployment aligns with findings from the African Economic Outlook (2012) which reported high rates of underemployment and discouragement among younger tertiary graduates. These findings suggest a disconnect between the education system and labor market demands, highlighting the need for better alignment of academic programs with industry requirements. Additionally, they point to the importance of policies and interventions aimed at addressing skills mismatches and enhancing job quality for graduates, to prevent underemployment and improve overall employment outcomes for young people in the region.

Gender disparities were evident in the study, with female graduates representing a larger portion of the unemployed compared to males, supporting the African Economic Outlook (2012) and Stats SA (2015). An article by Jubane, (2020) also reports higher unemployment rates among young women in South Africa, highlighting the challenges they face in the labor market. These findings underscore the need for targeted interventions to address gender-specific barriers to employment, such as gender bias in hiring practices, limited access to professional networks, and societal expectations.

Age was also a significant factor, with younger graduates (21–24 years old) more likely to be unemployed (46.2%), followed by those aged 25–29 and 30–35. The Pearson χ^2 test confirmed a significant association between age and employment status, echoing findings by Altbeker and Storme (2013) and Zimmerman et al. (2013) that younger graduates often face greater challenges due to a lack of experience. Younger graduates, especially those without prior work experience, may find it more difficult to secure employment as many employers prioritize candidates with practical experience. This highlights the importance of early career support initiatives, internships, and apprenticeship programs that can help younger graduates gain relevant work experience and improve their employability.

Modular courses, which are often designed to be more flexible and tailored to specific industries or career goals, may allow students to gain practical, hands-on experience through internships and project-based work. This practical focus can enhance the students' employability, as it adds to the academic achievement and aligns their learning more closely with job market demands (Carnevale et al., 2018). On the other hand, non-modular courses, which tend to have a more traditional, rigid structure, might not offer the same opportunities for industry-specific learning and networking. This could mean that graduates of non-modular courses might have fewer chances to demonstrate work experience or build personal networks, which are also crucial in determining earnings (Becker, 2020).

Modular courses are designed to equip students with specific skills that align closely with current job market demands, potentially reducing unemployment durations (Lusher et al., 2021; Glover et al., 2022). These courses emphasize practical competencies, making graduates more attractive to employers and facilitating quicker job placement (Kim et al., 2023).

In contrast, non-modular courses typically provide a more comprehensive, in-depth education over a fixed period. While they offer a holistic understanding of a subject, they may not always align with immediate labour market needs. As a result, graduates from non-modular programs may experience longer unemployment durations, particularly if their qualifications do not directly match employer requirements or if they lack specialized skills (Brown & Hesketh, 2019; McGrath & Yamada, 2023).

William et al., (2022) argues that non-modular courses in traditional disciplines might not always integrate practical skills or industry-specific knowledge, potentially impacting the speed at which graduates find relevant employment.

The effectiveness of job search strategies is another crucial determinant of employment outcomes. Studies by Caliendo (2015) and McGee (2015) suggest that an active and persistent job search strategy characterized by early and frequent applications is linked to faster employment. Card et al. (2015) further highlight that intensive job search efforts, including submitting a higher volume of applications, correlate with improved employment prospects.

Conversely, some scholars argue that job search intensity alone may not guarantee quicker employment. DellaVigna et al. (2022) suggest that factors such as individual motivation, industry demand, and external economic conditions also influence the success of job-seeking efforts. This implies that while proactive job searching increases the likelihood of securing employment, its effectiveness may vary based on contextual factors.

Geographical mobility has been identified as an important factor influencing employment speed, particularly in relation to urban migration. Buch et al. (2014) find that mobility to urban areas significantly improves access to job opportunities, given the higher labour demand and availability of professional networks in such regions. Urban areas often provide a broader range of employment options, which could expedite job placement for graduates.

However, contrasting perspectives suggest that migration does not always lead to better employment outcomes. De Brauw et al. (2014) argue that older graduates tend to secure jobs more quickly due to their work experience and strategic job-seeking approaches rather than mobility alone. Similarly, D'Amuri and Peri (2015) contend that migration may sometimes result in overqualification or job mismatches, potentially leading to suboptimal employment conditions. These findings challenge the assumption that geographical mobility consistently enhances employment prospects.

Poor academic performance has been found to prolong the job search process, aligning with Phillips' (2017) findings that failing grades negatively impact employment outcomes. Weak academic results may signal a lack of necessary skills or preparedness, making it more difficult for graduates to secure jobs.

Contrarily, Hovdhaugen (2015) suggests that academic performance is not always the primary determinant of employment success. According to Hovdhaugen, work experience, networking, and personal attributes may play a more decisive role in employment outcomes, challenging the notion that academic performance is a critical factor in securing jobs. These findings indicate that while exam grades influence employability, other factors may offset their impact.

Studies have shown that modular programs are often designed to be more responsive to labour market needs, offering practical and relevant skills (Klein & Tuma, 2019). These programs allow students to tailor their education to specific industries or career goals, which may improve their job prospects and earning potential (Harris & Smith, 2016). However, some research suggests that the long-term benefits of modular programs depend on industry-specific demand and the availability of relevant job opportunities (Collins et al., 2020). In contrast, other studies highlight that the prestige of the institution or the professional network it provides may have a greater influence on earnings than the format of the program (Hoxby, 2017).

Other studies on mentorship programs in different regions reveal mixed results regarding their impact on career outcomes. For instance, Bertrand, Crépon et al. (2021) found that combining formal apprenticeship training with classroom education led to higher earnings for participants in Côte d'Ivoire. Similarly, Alfonsi et al. (2020) observed that vocational trainees in Uganda earned lower incomes in the short term compared to participants in other training programs.

Research by Blau and Kahn (2017) and Goldin (2014) highlights that even in similar educational contexts, women face lower wages due to factors such as discrimination, occupational segregation, and limited career progression opportunities. Some scholars, like McKinsey & Company (2020), suggest that gender differences in negotiating salaries or choosing lower-paying industries may partially explain the wage gap. However, other research emphasizes that structural inequalities, including unconscious biases and disparities in promotions, are significant drivers of the gender wage gap (Booth et al., 2019). These findings align with broader trends and reinforce the persistent challenge of achieving gender pay equity.

Moreover, while academic performance, such as exam grades, is important in both types of courses, it may not fully explain earnings disparities between graduates from modular and non-modular courses. Graduates of modular courses may have more direct exposure to work environments and industry connections, potentially giving them a higher starting salary despite similar academic achievement (Lemieux, 2018). In contrast, non-modular graduates may face more challenges in translating academic success into higher earnings, especially if their education has not provided as many industry-specific opportunities. Therefore, while academic performance remains an important determinant of earnings, the structure of the course modular or non-modular adds complexity to the factors influencing graduates' financial outcomes.

Studies indicate that married individuals often benefit from greater financial stability and higher earnings potential, largely due to shared resources and the possibility of dual-income households (Korenman & Neumark, 2019). Additionally, marriage has been linked to increased access to stable employment and career advancement opportunities, further enhancing earnings prospects (Schultz, 2017). However, the extent of the marriage premium on earnings varies based on factors such as education level, occupational type, and age (Smock et al., 2019). While research broadly supports the positive correlation between marriage and earnings, these variations suggest that marriage alone is not a definitive determinant of higher income, as broader socio-economic factors also play a crucial role.

2.2.4.2 Level of STEM Academic Programs

The level of stem academic programs is one of the key factors that influence labour market outcomes. Higher-quality STEM education equips graduates with specialized skills that enhance employability, competitiveness, and career advancement. Moreover, the sector in which graduates are employed, the duration of employment, and their earnings are significantly impacted by the rigor and relevance of their STEM training.

Holmes, (2011) argues that societal values on reward for higher education are largely a function of the employment outcomes of graduates. Müller & Gangl (2003), suggest that an individual's level of education significantly influences their employment prospects in Europe. Additionally, school quality when controlling for education level may impact one's ability to secure and retain a job. The quality of education, including teaching resources and institutional support, can affect job search effectiveness and career stability.

Mpendulo & Mang'unyi, (2018) conducted a study in South Africa, revealing a positive relationship between education level and employment opportunities. Their findings indicated that the higher the level of education, the better the chances of securing employment. However, the study was based on a limited sample of 120 respondents from the Eastern Cape, South Africa, and did not address factors such as institutional influences, the field of study, or the nature of academic programs undertaken by individuals in relation to their labor market outcomes.

This study aligns with the findings of Gibbon, Muller, & Nel (2012), who noted that limited post-school options in South Africa restrict learners' opportunities for post-secondary education, thus limiting their prospects to low-level jobs. The implications for employment status are significant, as individuals with lower levels of education are more likely to be confined to low-quality jobs or face unemployment. This cycle perpetuates poverty and inequality, particularly for children from disadvantaged backgrounds, who are more likely to remain trapped in low-paying or unstable employment.

Kotey (2024) and Mashongoane (2015) argue that higher levels of academic certification enhance employment prospects within the same field of study. Williams (2023) and Fletcher et al. (2017) suggest that extended training periods may delay entry into the labour market or result in skills misalignment, thereby decreasing the chances of remaining in the same field.

Jepsen et al. (2014) and Dadgar & Trimble (2015) found that the level of academic certificate does not significantly affect the employment outcomes of graduates employed in a field different from their area of study. However, when accounting for factors such as geographical mobility, job search intensity, and the volume of job applications, their findings indicated a more significant impact of these variables in securing employment.

Laird (2017) and Bullock et al. (2018) found that marital status can influence employment outcomes, particularly in the private sector. Their findings suggest that marital status may be associated with greater stability or economic responsibility, making individuals more attractive to private employers. Ertas (2016), argued that younger employees bring flexibility and technological adaptability, traits highly valued by private sector employers, potentially enhancing job prospects and stability.

Hansen et al. (2024) and Kittelsen & Helland (2017), found out that higher academic performance is generally linked to better employment prospects, especially in the private sector. Araki et al. (2016), suggested that graduates from elite institutions who tend to have higher academic performance are often promoted rapidly within companies due to their perceived superior job performance. This discrepancy highlights the complexity of the relationship between academic performance and employment outcomes, which may be influenced by industry type, job role, or other contextual factors.

Do Monte (2017), argues that in certain contexts, education and migration may not always have a direct effect on private sector employment outcomes. However, Leyaro & Joseph (2019) offer a contrasting perspective, arguing that returns on investment in technical and vocational education and training (TVET) are relatively low. Their findings indicate that TVET qualifications do not necessarily translate into better job opportunities in the private sector, possibly reflecting a misalignment between the skills provided in vocational programs and those demanded by employers.

The recent rise in youth unemployment in Kenya and globally raises the question of whether education can play a job-allocation function and help guard against unemployment. The study by (Kuepie & Nordman, 2016) suggests that education opens the door for graduates to enter the most profitable niches, found in both the public and private sectors of the economy. On the other hand, (Livanos & Nuñez, 2016) in their study to establish the role of quality of higher education in the labour market outcomes of graduates, found that education is a major enabler towards employment in various sectors.

Defloor, Van Ootegem, & Verhofstadt (2015) posit that the quality of an individual's first job depends significantly on personal effort. However, this effort is largely influenced by factors such as educational attainment and the state of the labour market, as well as the sector of employment. Edgerton *et al.,* (2012) suggest that academic credentials in the labour market serve as a signal to employers of an individual's pathway of achievement and their potential for future performance as an employee. They further argue that vocational credentials specifically indicate that an individual is formally qualified, having completed the necessary training, for a particular job within a specific sector.

Tomlinson (2017)) observes that there are strong connections between a graduate's formal education performance and their future employment, particularly through the development of skills acquired via subject specialization, technical knowledge, and career-building abilities. High academic performance is viewed as a solid foundation for individuals entering the workforce, as those with exceptional academic achievements often possess a deeper concentration, more specialized knowledge, and expertise in their field (Omar, Bakar, & Rashid, 2012).

This suggests that individuals with higher levels of academic performance are more likely to be motivated to enhance their employability by further developing their skills and knowledge, whereas individuals with lower academic achievements may be more hesitant when it comes to choosing and determining their career paths. This aligns with the view of Omar, Bakar, & Rashid (2012). Yunus (2018), found no statistical significance between certification levels and self-employment in unrelated fields. He further established that for individuals who are self-employed within their field of study, the level of academic certification remained statistically insignificant. Zając (2018), argues that older individuals may possess greater experience, maturity, and an entrepreneurial mindset, making them more inclined to pursue self-employment in fields unrelated to their formal education.

Neumark et al. (2019) and Jackson & Wilton (2017) argue that older individuals leverage their accumulated experience, maturity, and established professional networks to secure employment more efficiently. Their possession of transferable skills, industry-specific knowledge, and strategic job search approaches enhances their attractiveness to employers, contributing to shorter unemployment durations compared to younger job seekers.

Koubi et al. (2016), observed that migrants often face delayed employment outcomes due to geographical mobility, adapting to new labour markets, cultural barriers, and the absence of local professional networks. Wakeling & Laurison, 2017 opines that degree holders are more attractive to employers due to their specialized expertise. However, graduates from national polytechnics, which offer qualifications below a degree level, face greater challenges in entering the job market. For these graduates, success largely depends on acquiring hands-on skills that align with industry-specific demands, as practical experience often compensates for the lack of advanced academic credentials.

Symeonaki & Filopoulou (2017), highlighted gender-based differences in employment outcomes. They argue that shorter employment transition period for men may be attributed to factors such as gender biases in hiring, societal expectations, or greater access to professional networks that facilitate job placement. This disparity underscores the need to consider gender as a key variable in employment trajectory analyses, as it directly influences the rate at which individuals transition from unemployment to employment in whichever sector.

Kuepie and Nordman (2016) did a study in the Republic of Congo, which showed that unemployment initially increases with the level of education, but then decreases once individuals complete secondary school and enter higher education. Their findings suggest that individuals without the minimum level of schooling are less likely to experience unemployment compared to those who have at least completed primary school. However, the study did not examine the effects of post-tertiary education on labour market outcomes, nor did it consider the nature of academic programs undertaken by the respondents. Additionally, the study did not address the role of the field of study or demographic factors in influencing employability or unemployment. These omissions limit the comprehensive understanding of how education level, field of study, and demographic characteristics impact employment outcomes.

Van der Merwe and van Reenen (2016), noted that educational attainment is included to allow for differences in human capital between individuals. The intuition is that regardless of an individual's current labour market state, those with higher levels of educational attainment are more likely to be employed in the next period than others. The degree of educational attainment is specified as a series of dummy variables that distinguish whether an individual has a degree (bachelor or higher) or diploma, vocational training or has not completed high school. The study did not put into consideration what the effect is of the field of study on labour outcomes and the sociodemographic factors that surround getting employment.

The study by Van-der-Merwe (2016) explores the relative importance of individual characteristics and circumstances in one year in determining the probability of being in a particular labour market state the following year. The results indicate that the most important factors for increasing the likelihood of being employed in the year ahead include being currently employed, having tertiary qualifications, and being a male with dependent children. The latter is likely capturing traditional gender and family caregiving responsibilities, which have made males more likely to be employed than females. In contrast, factors that negatively affect the probability of being employed in the year ahead include being a female with dependent children, having a long-term health condition, not completing high school, and being a migrant from a non-English-speaking background.

Over the past decade, the marginal effects associated with being female, older, and already employed have changed considerably. This shift likely reflects changes in work and family preferences, concerns over job security, and broader macroeconomic trends. While the study accounted for sociodemographic factors like age and gender, it did not examine the effects of the nature of the academic program or the field of study on labor market outcomes.

Individuals with higher education qualifications have generally been able to find employment more quickly, secure well-paying jobs, and develop rewarding career paths. They are also better positioned to adapt successfully to changes in the labor market. This labor market success enables individuals to not only meet their own basic needs but also to support a family, pursue personal interests, engage in leisure activities, and achieve long-term goals OECD (2014).

The relationship between academic certification and earnings has long been a subject of debate in labour economics. Traditional human capital theory posits that higher educational qualifications lead to increased earnings by providing individuals with better job opportunities, higher wages, and greater job security (Kahn, 2018; Mirowsky, 2017). However, (Marginson, 2019; Bowen, 2018) findings challenge this assumption, particularly in the context of Technical and Vocational Education and Training (TVET). They argue that the level of academic certification whether craft, diploma, or higher diploma is not always a significant determinant of earnings. Instead, factors such as work experience, skill acquisition, and industry demand often play a more crucial role in shaping earning potential within technical fields (Vincent & Rajasekhar, 2023; Wongmonta, 2023).

In many developing economies, the labour market for TVET graduates tends to prioritize practical experience over formal qualifications. Industries frequently emphasize job-specific competencies rather than academic credentials (Kebede et al., 2024). This perspective aligns with the arguments of Jensen and Kler (2018), who found that in certain technical sectors, hands-on experience can be more influential than formal education in determining job placement and income levels. Moreover, in oversaturated job markets, the link between education and earnings becomes increasingly blurred, with many graduates facing underemployment or securing jobs that do not match their qualifications (Lavrinovicha, 2015; Pascual-Sáez, 2023). These realities suggest that while academic certification remains important, it does not necessarily guarantee higher earnings, especially in skill-based industries where experience and market demand exert greater influence.

Employment category further emerges as a critical determinant of earnings. Individuals engaged in training programs, employed in different fields, or self-employed within their specialized areas tend to earn more than their unemployed counterparts. This underscores the value of workforce engagement in shaping financial outcomes (Bureau of Labor Statistics, 2020). Self-employment, in particular, is associated with financial independence and, in some cases, higher earnings compared to traditional employment structures (Simoes et al., 2016; Falco & Haywood, 2016). Additionally, individuals who transition into careers outside their initial field of study or participate in skill-enhancing training programs often acquire unique competencies that increase their marketability and earning potential (Yang, 2018). These insights highlight the importance of active labor market participation in ensuring financial stability and career progression.

Beyond education, social and demographic factors also shape earnings potential. Marriage has been identified as a contributing factor to financial stability, as it provides access to additional resources that enhance earning capacity. Research indicates that marriage fosters economic benefits through shared household expenses and dual-income opportunities, thus improving financial security (Shamblen, 2018). Furthermore, married individuals tend to experience greater economic stability, which can translate into career growth and better job prospects (Zhang, 2014). The psychological and social support associated with marriage may also positively impact career performance, leading to improved earnings outcomes (DeMaris & Oates, 2022). These findings underscore the role of marital status in influencing economic well-being and financial success

Edgerton, Roberts and von Below (2012), argue that the higher the level of education, the higher the productivity of workers. Eurostat (2019), show that, in the EU, employees with higher education levels earn significantly more. Median gross hourly earnings of individuals with a high level of education were almost 50% higher than those with a medium level of education (secondary education), and 70% higher than those with only primary school qualifications. This indicates that higher education not only enhances productivity but also improves employability, making individuals more competitive in the labor market.

The implications for employability and earnings are clear individuals with higher education levels, particularly those with relevant fields of study and quality academic programs, are likely to have better chances of securing stable, higher-paying jobs. Furthermore, the level of education directly impacts the potential for increased earnings. Those with advanced qualifications and specialized fields of study tend to command higher salaries due to their specialized skills and higher productivity. Therefore, the nature of one's academic background, including both the level and field of education, significantly contributes to better employment outcomes and earnings potential.

Diaconu (2014), conducted a study on education and labour market outcomes in Romania, finding that the level of education is positively linked to both employment rates and income levels. The study, which also included other EU states, revealed that higher levels of education increase the chances of securing employment and result in higher earnings. University graduates had the highest employment rates, with over 80% employed, while only 60% of those with upper secondary and post-secondary education, and about 40% of those with pre-primary, primary, and lower secondary education were able to find a job. The study also indicated that individuals with higher education levels tend to earn higher wages compared to their less-educated counterparts. However, the study did not consider the impact of the academic program or the institution attended, nor did it account for other factors such as age, marital status, or location. Additionally, while the study provides valuable insights within the European context, its generalizability to other regions, particularly Africa, is limited due to differences in funding, GDP, and economic conditions.

The study aligns with the OECD report, which highlights that higher education graduates, on average, earn more than individuals with lower educational attainment. However, the earnings of graduates can vary significantly from person to person. Across OECD countries, 28% of working-age higher education graduates earn less than the median earnings in their country, and a third of these low-income graduates earn less than half the median (OECD, 2015).

Holding a higher education qualification is closely linked to higher earnings, labour market security, and a good working environment (Cazes, Hijzen, & Martin, 2015). OECD (2010) further showed that people who hold higher education credentials are more likely to engage in activities such as voting, charitable giving, and volunteerism.

Alina (2012), showed that education may influence several labour market outcomes, such as wages and earnings, the time to the first stable job, employment/ unemployment, worker productivity, hours worked, nature of work, worker's health and fringe benefits. The findings also showed that the mechanisms by which education affects labour market outcomes are diverse and included years of schooling, educational level attained, attainment of a particular credential, educational system, investments in education, schooling quality, individual's educational track, parents' educational track, curriculum type and sector of activity.

Akcan, (2023) investigated teachers' perspectives on the impact of STEM education on the labour market through a qualitative case study approach, involving semi-structured interviews with 32 teachers. The study found that STEM education was seen as a key driver of job creation, entrepreneurship, and improved employment prospects. It also helped mitigate social costs, brain drain, and other societal issues. Teachers highlighted that STEM education equipped students with essential 21st-century skills, including creative and critical thinking, making them more adaptable and prepared for future careers. However, concerns about potential technological unemployment due to advancements in these fields were also raised. The study emphasized the need for early integration of STEM subjects into the curriculum and investment in teacher training and infrastructure to fully realize their benefits. By fostering innovation and addressing labour market inequalities, STEM education was viewed as a vital pathway to economic growth and societal well-being (Akcan, 2023).

Despite substantial institutional efforts to recruit students into Science, Technology, Engineering, And Mathematics (STEM) fields, the rate of students choosing careers in these areas remained persistently low. An analysis using data from the Educational Longitudinal Study employed a two-level model to examine factors influencing high school sophomores' decisions to pursue careers in these disciplines. The study explored a range of predictors including gender, math self-efficacy, socio-economic status (SES), school type, and urbanicity. Findings highlighted that, even with the advantages provided by private schools, a significant gender gap persisted (Ketenci, Leroux, & Renken, 2020). Female students with high math self-efficacy were still less likely than their male counterparts to choose careers in these fields. The study demonstrated that males in private schools with high SES and math self-efficacy were more likely to pursue related careers, underscoring the impact of gender and contextual factors on career choices.

The stark contrast between the growing demand for professionals in these areas and the insufficient number of students prepared for such careers was evident, particularly in the United States. Reports indicated that only 44% of high school students were ready for college-level math and 36% for science, leading to low degree attainment in these fields among undergraduates (Ketenci, Leroux, & Renken, 2020). This issue was exacerbated by a persistent gender gap, with women being underrepresented in disciplines such as engineering, computer science, and physics. Existing research often focused on either individual factor like race, gender, and socio-economic status or contextual factors such as school type and urbanicity. However, few studies simultaneously examined these factors, highlighting the need for a more integrated approach to understanding career choices in these areas. Additionally, the level of education attained further influences job opportunities, career progression, and income levels, necessitating a comprehensive analysis of its impact on labour market outcomes across different fields of study.

2.2.4.3 Academic Field of Study

The increasing demand for technological and scientific expertise has led to a notable rise in enrolment in Science, Technology, Engineering, and Mathematics (STEM) fields. (UNESCO, 2016) attributes this growth to the global emphasis on innovation and the evolving labour market, which increasingly prioritizes digital and technical skills. Despite this shift, humanities and social sciences continue to play a crucial role in fostering critical thinking, cultural awareness, and societal development, though their enrolment rates remain comparatively lower than those in STEM disciplines(WEF, 2019; GMAC, 2019).

Similarly, the health and medical sciences fields have experienced significant growth, driven by the need to address global health challenges and the increasing demand for healthcare professionals' challenges (WHO, 2016) (ACGME, 2020). Education programs, while maintaining steady enrolment levels, remain vital due to the persistent need for qualified educators to support quality learning outcomes (OECD, 2021; NCES, 2018). These trends highlight the dynamic nature of higher education enrolment patterns and the critical role of academic sponsorship in ensuring students have access to opportunities that align with evolving labor market demands across diverse disciplines.

The field of study refers to an individual's academic orientation and plays a crucial role in determining when, where, and how quickly one gains employment. Understanding its significance can provide insights into labour market outcomes and career trajectories. Career decision-making is a process that every individual must navigate, particularly fresh graduates from educational institutions (Chai et al., 2013) . A study by Gossett, Chinyoka and Obasi (2016) highlighted that career decisions are critical in shaping employment opportunities, as they influence the likelihood of securing a job in a competitive labour market.

The influence of field of study on employment outcomes varies across different employment categories. Di Paolo and Matano (2022), who argue that pre-graduation work activities related to the field of study have a stronger impact on employability and job stability than the academic discipline itself. This suggests that practical experience such as internships, apprenticeships, and job placements play a more crucial role in determining employment outcomes than formal education alone.

The increasing emphasis on transferable skills and the growing flexibility of the labour market further explain why field of study may not always be a decisive factor in securing employment. Individuals are increasingly able to transition across fields based on competencies rather than strictly adhering to their academic specialization. Other variables, such as migration patterns, academic qualifications, and job search intensity, may also overshadow the direct impact of field of study on employment outcomes.

Montt (2017) noted that labour market saturation can restrict graduates' ability to enter self-employment within their specialization, as an oversupply of professionals in certain fields may reduce demand for their services. Furthermore, the transferability of skills across different industries plays a crucial role in shaping self-employment opportunities.

Fields with highly transferable skills allow for a broader range of entrepreneurial ventures, whereas specialized fields with fewer transferable skills may limit graduates' options for self-employment. The incidence of field-of-study mismatch and overqualification is also relevant, as individuals with highly specialized training may struggle to find employment that aligns with their qualifications, potentially driving them toward self-employment. These findings highlight the importance of considering labor market conditions, skill adaptability, and industry saturation when evaluating the relationship between field of study and employment trajectories.

Wu (2012) notes that the expansion of higher education has led to an oversupply of college graduates, resulting in a highly competitive labour market. The transition from school to work is a critical phase for graduates, as leaving student life behind and entering full-time employment requires key career-related decisions that can shape their future career success (Ng & Feldman, 2007; Feldman, 2007; Hoye & Saks, 2008). These studies highlight the importance of examining the impact of a graduate's field of study on labor market outcomes.

Stojanová and Blašková (2014) conducted research on the role of graduates' field of study and its impact on the transition to working life. Their study addresses key questions regarding the relationship between a graduate's chosen field of study and their ability to find a suitable job, meet expectations for job content and position, and achieve adequate remuneration. The research aimed to explore the graduates' chances of success in the labour market following the completion of their chosen field of study. The authors formulated three hypotheses regarding the practical application of graduates based on their field of study. One key finding from their research revealed the significant impact of field selection on graduates' job prospects. Notably, 60% of respondents had focused on economics and humanities, fields that significantly exceeded the labour market's absorption capacity. In contrast, graduates of technical and natural sciences faced fewer difficulties in finding employment and reported the process as relatively easy. This suggests that the field of study plays a crucial role in determining the ease of transition to the labor market.

Stojanova & Blaskova (2014), concluded that opportunities for graduates of tertiary education are closely linked to the economic development of the country, the dynamics of employment creation, and thus their success in the labour market. However, the most significant factor is individual access to motivated enforcement and, especially, the rational choice of field of study. Ayuka (2020) investigated the role of education level and course of study on employment chances in Kenya. Using a multinomial logit model, Ayuka found that career/field of study choice is influenced by sociodemographic factors, and that the field of study significantly affects employment. However, the study did not account for the role of institutional partnerships, internship placements, and the nature of academic programmes undertaken by graduates.

TVET's role in addressing unemployment through skill-based education has been well-documented. According to the study, TVET programs equip students with relevant skills that meet the demands of the job market, thereby reducing unemployment. The success of TVET in countries like Germany and China, where vocational training is highly regarded, further underscores its potential in improving employment outcomes World Bank, (2018). The study recommended greater awareness and promotion of TVET among the youth to bridge the gap between education and employment. Despite the proven benefits of TVET, there has been a significant lack of awareness and uptake among Kenyan youth (Nason, 2019). The study found that the majority of the youth were unaware of TVET programs, highlighting a critical area for policy intervention. Enhancing awareness and accessibility of TVET could potentially transform the employment landscape by aligning educational outcomes with market demands. This approach is crucial for addressing the high rates of unemployment and underemployment among graduates from non-technical fields.

The study emphasized the need for a paradigm shift in educational priorities toward skill-based and vocational training to combat youth unemployment in Kenya. These findings align with global observations on the importance of matching educational outcomes with labour market needs (Nason, 2019). By promoting and enhancing TVET programs, policymakers could improve employment rates among graduates and address the chronic issue of skill mismatch in the job market.

The study published in the *AfriTVET Journal* highlighted that youth unemployment, particularly among graduates, remains a significant concern (Nason, 2019). It revealed that many graduates, especially those from non-technical fields, faced challenges in securing employment. This high unemployment rate among graduates underscores a critical mismatch between the skills acquired through higher education and those demanded by the labour market, a trend consistent with global observations by the World

Bank (2018) and the International Labour Organization (ILO, 2020). The study emphasized the stark disparity in employment rates between graduates from technical and vocational education and training (TVET) programs and those from other academic disciplines. TVET graduates, who are equipped with practical and industry-relevant skills, were found to have better prospects in the job market, highlighting the growing importance of vocational training in addressing youth unemployment.

King and Palmer UNESCO-IIEP (2007) and Zachary et al. (2024) argue that higher educational attainment, particularly in skill-driven fields, correlates with better employment outcomes. This is supported by the study, which found that TVET graduates had a much lower unemployment rate (12.5%) compared to non-TVET diploma holders (93.75%) and degree holders (80%). The effectiveness of TVET in bridging the skills gap was further reinforced by the high employability of its graduates. The issue of skill mismatch, which is not unique to Kenya, is a global phenomenon. Linotte (2018) and the World Economic Forum (2019) discussed how the rapid growth in the youth population and improved access to higher education had exacerbated unemployment. Many graduates held qualifications that did not align with market demands, leading to high unemployment rates despite the increasing number of educational institutions.

According to (ILO, 2016) TVET programs equip students with the practical skills that are directly aligned with labour market needs, which helps reduce unemployment by improving employability. The ILO’s research emphasizes that countries with strong vocational training systems, such as Germany and China, see positive employment outcomes, as these systems ensure that graduates are ready to meet the demands of various industries.

Similarly, Nason (2019) observed that in Kenya, there was a significant lack of awareness and uptake of TVET programs among the youth, despite the proven benefits of skill-based education. This gap presents an urgent area for policy intervention. Nason’s study noted that many Kenyan youth are unaware of the opportunities that TVET offers, contributing to a mismatch between the skills acquired in formal education and those demanded by the labor market. Increasing awareness and improving access to TVET programs could bridge this gap, transforming the employment landscape by aligning educational outcomes with labor market needs. This approach is particularly critical for addressing the high rates of unemployment and underemployment among graduates from non-technical fields.

The study’s findings echo global observations made by the ILO (2016), which advocates for a shift in educational priorities toward skill-based and vocational training. According to the ILO, this shift would not only combat youth unemployment but also ensure that the workforce is equipped with the technical skills necessary to thrive in an ever-changing global economy. By promoting and enhancing TVET programs, policymakers can effectively address the chronic issue of skill mismatch in the job market and improve employment outcomes for youth.

(Koros, 2021) highlights that many employers find that university graduates, particularly those with bachelor's degrees, often lack the specific skills required by the job market. This mismatch has led to a steady decline in employment rates for Bachelor’s degree graduates, as evidenced by recent trends in youth employment statistics. In response to this, many youths are opting to pursue higher education, specifically Master's degrees or TVET (Technical and Vocational Education and Training) courses, to avoid the phenomenon of 'degree inflation.' These avenues are becoming increasingly popular strategies for enhancing employability, as they provide skill-based qualifications that align more closely with labor market demands. This shift has resulted in a growing number of employed youths with Master's degrees or TVET qualifications, indicating a potential shift in educational aspirations to meet labor market needs

The methods of securing employment for polytechnic graduates reveal important insights into both opportunities and challenges in the job market. According to the Tracer Study Report for the Financial Year 2023 (TSRFY, 2023), 34.48% of graduates found their jobs through personal recommendations, while 17.24% secured employment through direct applications. These findings highlight the critical role of personal networks and proactive job-seeking methods, such as leveraging professional connections, in securing employment. Job-seeking through referrals and direct applications often offers a quicker and more reliable route to employment.

However, the absence of referrals from the polytechnic’s Career Services indicates a potential gap in institutional support for graduates' job placement. This suggests that universities and training institutions need to strengthen their connections with employers to enhance their graduates' employment outcomes. Providing career services that facilitate networking and job placements could greatly benefit graduates by improving their access to opportunities.

In terms of employer contacts, the study revealed that securing employment typically required between 0-5 employer contacts for 50% of graduates, while 20.69% needed 6-10 contacts. This disparity shows that while many graduates find jobs relatively easily, others encounter more challenges in navigating the job market, requiring them to engage with a larger number of employers to secure employment.

Graduate employment within their field of study was another positive outcome, with 62.3% employed in roles related to their training. This indicates that polytechnic programs align well with job market requirements, and many graduates are able to transition directly into jobs that match their qualifications. Examples of jobs that can be easily found by polytechnic graduates include positions in fields such as electrical engineering, plumbing, hospitality management, and mechanical repairs. These roles tend to have a higher demand in the private sector, where vocational skills are often valued.

However, challenges remain for some graduates, particularly those in less technical fields or in areas where job opportunities are scarce. For instance, graduates in fields like tourism or business administration may struggle to find employment in rural areas, where there is limited industry and fewer job openings. Moreover, the increasing competition in certain sectors, such as IT or graphic design, may require additional efforts from graduates to distinguish themselves in the labor market, such as through further specialization or gaining practical experience through internships.

The report *The Employment Trajectories of Science, Technology, Engineering, and Mathematics (STEM) Graduates* by a Smith and White (2018) offers an in-depth analysis of STEM career pathways in the graduate labour market. The study utilizes data from several national sources, including the Higher Education Statistics Agency (HESA), the Annual Population Survey (APS), the 1958 National Child Development Study (NCDS), and the 1970 Birth Cohort Study (BCS). This comprehensive research addresses the ongoing debate about the STEM skills deficit, exploring several critical questions: the immediate and long-term career destinations of STEM graduates, a comparison of employment patterns between STEM graduates and those with non-STEM degrees, and the impact of individual characteristics on STEM career participation (Smith & White, 2018).

The findings indicate that the career destinations of STEM graduates have remained notably stable over time, despite significant changes in higher education policy and economic conditions. The study reveals that STEM graduates typically secure graduate-level employment shortly after graduation. However, specific fields such as computer science and engineering still exhibit higher unemployment rates compared to other disciplines, suggesting ongoing concerns about skill shortages in these areas. The study identifies two primary employment pathways for STEM graduates: one leading to highly skilled STEM roles and another leading to routine occupations or unemployment. It also highlights that graduates from prestigious universities are more likely to secure high-skilled STEM jobs compared to their peers from less well-known institutions (Smith & White, 2018).

When examining the occupational positions of older STEM graduates, the report finds that while a significant majority remain employed in graduate-level jobs, only about half hold high-skilled STEM positions. The study reveals a notable discrepancy between the employment outcomes of biological science graduates and those in engineering and ICT fields. Biological science graduates are less likely to secure STEM jobs, and this trend persists into their later careers. The report also indicates that professional engineering and

ICT roles are primarily filled by graduates from those specific disciplines, limiting the integration of graduates from other STEM backgrounds (Smith & White, 2018).

Long-term career trajectories show that STEM graduates experience substantial movement out of high-skilled STEM roles as they age, with limited evidence of late-career entry into these positions. In contrast, sectors like education and health retain graduate workers more effectively. The report suggests that attracting older STEM graduates back into high-skilled roles could help address workforce shortages. Furthermore, it highlights that many high-skilled STEM positions are occupied by non-graduates, indicating that educational qualifications are not always a prerequisite for these roles (Smith & White, 2018).

The report concludes that STEM graduates do not necessarily enjoy a clear employment advantage over their non-STEM counterparts. By age 30, the employment patterns of STEM and non-STEM graduates are quite similar, with both groups securing graduate-level positions. The study also finds that the majority of highly skilled STEM jobs are held by non-graduates, challenging the focus on increasing the number of STEM degree holders. This suggests that alternative pathways, such as apprenticeships and vocational training, may be crucial to addressing the STEM skills gap (Smith & White, 2018).

According to Khainga & Mbithi (2018), the employment rates of graduates from different academic fields of study within national polytechnics in Kenya reveal significant sectoral variations. The public sector employs a substantial proportion of youth graduates, accounting for 40% of the employed youth population. This preference for public sector employment is primarily driven by job security and pension benefits, as reported by the

World Bank (2018). In contrast, self-employment among youth remains low at 4%, largely due to a lack of capital and the experience necessary to transition into self-employment.

In Kenya, graduate unemployment has been steadily rising, with employers often highlighting skills mismatches and a lack of labour market information among university graduates as the primary causes (Education Act, 2007; Ministry of Education, 2017). The findings of this study indicate a consistent decline in employment rates for Bachelor's degree graduates, with many youths opting to pursue Master's degrees to escape the "degree inflation" trap. This shift has resulted in a growing number of graduates with advanced degrees entering the labour market. However, the rising educational attainment, particularly among university graduates, has had significant implications on the sector of employment. While university graduates are increasingly concentrated in certain sectors, technical and vocational education and training (TVET) graduates are securing jobs at a higher rate, particularly in skill-driven fields such as engineering, manufacturing, and construction.

TVET programs, which equip students with industry-relevant skills, have proven effective in bridging the gap between education and employment. Despite this, many youths continue to pursue higher academic qualifications without considering the potential benefits of TVET, contributing to sectoral imbalances in the job market. The trend emphasizes the need for a more strategic alignment between academic qualifications, TVET certifications, and the skills demanded by various sectors, ensuring that both university and TVET graduates are better positioned for sustainable employment opportunities.

Education levels significantly influence employment sector choices. Graduates with diplomas and bachelor's degrees often find employment in the private sector, particularly in industries such as retail, banking, telecommunications, and manufacturing. These sectors require specialized skills that align with the qualifications obtained through these programs. On the other hand, self-employment remains a less common choice for these graduates due to factors such as limited capital, lack of entrepreneurial skills, and inadequate access to funding.

Graduates with a bachelor's degree, however, are less likely to secure employment in the public sector, a trend often attributed to degree inflation and the rising demand for postgraduate qualifications (Grounds & Moore, 2017). As a result, bachelor's degree holders may struggle to compete for public sector roles, where higher qualifications, such as master's degrees, have become increasingly preferred.

In rural areas, despite the presence of opportunities in sectors like agriculture, small-scale businesses, and informal industries, the availability of employment in the public sector remains limited. Public sector jobs, such as those in education, healthcare, and government offices, are more concentrated in urban areas, where infrastructure, resources, and administrative hubs are located. Consequently, rural areas experience fewer opportunities for graduates to enter the public sector, limiting employment options for young people in those regions.

(Nyaga, 2010) argues that the skills acquired through education and experience play a crucial role in determining employment opportunities across various economic sectors. When there is a match between the skills acquired and industry expectations, the likelihood of securing employment in the public sector increases. In contrast, the private sector often offers training opportunities regardless of prior education, which may reduce the chances of public sector employment education (Nyaga, 2010). Age also significantly influences employment distribution, with youth aged 24-29 more likely to find employment in non-governmental organizations (NGOs). However, for individuals with lower educational qualifications, the transition to stable employment is often prolonged. Extended job search durations decrease the probability of finding paid employment, while simultaneously increasing the likelihood of pursuing self-employment.

Educational attainment is a key determinant in formal employment, with higher education levels enhancing the prospects of securing jobs in the private sector. Nevertheless, degree inflation has led to a reduction in the chances of public sector employment for individuals holding only a Bachelor's degree (Khainga & Mbithi, 2018) . Graduates from rural areas face additional challenges due to limited access to resources and job opportunities, often leading them to migrate to urban areas in search of employment.

Furthermore, job satisfaction plays a significant role in employment choices, with youth reporting higher levels of satisfaction in self-employment compared to public service positions. While wage and salaried jobs with legal contracts are attractive due to the job security they provide, contractual employment is less preferred compared to permanent positions. This indicates a preference for stable, long-term employment opportunities over short-term, insecure contracts.

Education and training play a critical role in enhancing productivity and improving employment prospects. Diploma and degree holders generally have higher chances of securing employment in the private sector. However, Bachelor's degree holders face challenges in public sector employment due to degree inflation, which has diminished the demand for non-postgraduate qualifications (Moore & Koning, 2016). Graduates from rural areas often migrate to urban centers in search of better employment opportunities, reflecting the disparity in access to resources between urban and rural areas. Job satisfaction is another vital factor influencing employment choices, with youth tending to prefer private sector jobs over public service positions, particularly when compared to self-employment. Furthermore, permanent positions are viewed as more attractive than contractual roles, offering greater job security and long-term career stability (Khainga and Mbithi's (2018)

Khainga and Mbithi's (2018) study offers a comprehensive analysis of the factors influencing youth employment distribution across various economic sectors in Kenya. It emphasizes the significant roles that education, experience, mentoring, and job satisfaction play in shaping employment outcomes. The study advocates for policy interventions to address skills mismatches, promote mentorship programs, and create inclusive labor laws that can improve the employment prospects for young graduates. It highlights the necessity for policies that support career growth opportunities, self-employment, and the expansion of private enterprises. Additionally, effective mentoring, networking programs, and initiatives like internships and apprenticeships are essential to preparing youth for the labor market and ensuring they possess the requisite skills and experience to meet industry demands.

The Tracer Study Report for the Financial Year 2023 (TSRFY, 2023) further complements these findings by analyzing the employment outcomes and the effectiveness of training programs for polytechnic graduates. The report highlights key insights into job search duration, employment methods, mobility, income, and the relevance of training programs. It reveals that a significant majority of polytechnic graduates specifically 93.11% secure their first job within 12 months of graduation, with 74.14% finding employment within six months. This relatively short job search duration reflects an effective job placement mechanism, suggesting that the training provided by the polytechnic institution aligns well with market demands. Notably, only a small fraction, 6.90%, cited the length of their job search as a major challenge, indicating that employment opportunities are generally accessible to graduates within a year of completion.

The length of unemployment is influenced by various individual and demographic factors beyond the field of study. Research by Kulik (2023), Smith and Taylor (2024), and Zhao et al. (2024) highlights that unemployment duration is shaped by a combination of socio-demographic characteristics and labor market dynamics.

They pointed out that the key determinants include age, where younger individuals tend to experience shorter unemployment spells due to higher labor market flexibility, whereas older workers may face longer periods of joblessness due to skills obsolescence or age-related biases. Gender disparities also persist, with women often encountering longer unemployment durations due to labor market discrimination, caregiving responsibilities, and occupational segregation.

Marital status further influences unemployment length, as married individuals may experience varying job search intensities depending on household financial stability and dual-income considerations. Additionally, immigration status plays a critical role, with migrants often facing structural barriers such as work authorization challenges, credential recognition issues, and limited social networks that prolong unemployment (Zhao et al., 2024).

Education levels also significantly impact the duration of unemployment, with higher educational attainment generally associated with shorter unemployment spells due to increased employability and access to a broader range of job opportunities. However, certain fields of study may lead to longer unemployment durations if they have limited job market demand or require additional certifications and work experience before employment.

Overall, these findings underscore that while field of study remains an important factor, unemployment duration is more comprehensively explained by a combination of demographic characteristics and labor market conditions, necessitating targeted policy interventions to address structural inequalities in employment access.

Jun (2017) conducted a study on "Factors Affecting Employment and Unemployment for Fresh Graduates in China," examining factors such as college reputation, field of study, and gender, which impact the job search prospects of graduates from Shandong Province. The research showed that graduates from research universities found jobs more quickly, and those in economics, management, or engineering fields had an easier time securing employment. Additionally, there was no significant gender gap in employment. According to Jun, the institution attended plays a major role in labour outcomes. However, the study did not explore how STEM factors (nature, field of study, teaching resources, and level of study) and other demographic factors interact to influence overall labour outcomes.

Youth unemployment is a pressing global issue, and Kenya exemplifies the severity of this challenge. According to (Nason, 2019) study published in the AfriTVET Journal, youth unemployment, particularly among graduates, remains a significant concern. The study highlighted that many graduates, especially those from non-technical fields, struggle to secure employment. This high unemployment rate among graduates indicates a mismatch between the skills acquired in higher education and those demanded by the labour market, reflecting global trends noted by Kraay (2018) and Singh and Ehlers (2020). The disparity in employment rates between graduates from technical and vocational education and training (TVET) programs and those from other academic fields was stark.

The study revealed that TVET graduates had a significantly lower unemployment rate (12.5%) compared to non-TVET diploma holders (93.75%) and degree holders (80%). This finding supports the argument put forth by King and Palmer (2007), Palmer (2017)and Zachary et al. (2024), that higher educational attainment, particularly in skill-driven fields, correlates with better employment outcomes.

McGrath et al. (2017) found that TVET graduates often face initial challenges in securing employment immediately after graduation but typically manage to find jobs within a few months to a year. Similarly, a UNESCO-UNEVOC report (2019) indicated that employment rates for TVET graduates vary significantly by region and industry, but generally, TVET graduates enjoy higher employment rates compared to their peers with general education.

The effectiveness of TVET in addressing the skills gap is further evidenced by the high employability of its graduates. The issue of skill mismatch is not unique to Kenya but is a global phenomenon, as noted in various studies. For example, Linotte, (2018) and the World Economic Forum (2019),) discussed how the rapid growth of the youth population and improved access to higher education had exacerbated unemployment. They argued that many graduates held qualifications that did not align with market demands, resulting in high unemployment rates despite the growing number of educational institutions.

In their 2018 study, Khainga and Mbithi explored the employment distribution of youth graduates in Kenya, with a particular focus on income disparities among graduates holding diplomas, bachelor's degrees, and master's degrees (Khainga & Mbithi, 2018) .The study examined how these educational qualifications impact employment opportunities across various economic sectors, highlighting the role of experience, technical skills, and mentoring in shaping employment outcomes.

Earnings outcomes across different fields of study exhibit significant variation, influenced by labour market demand, professional regulations, and job role diversity. Chetty et al. (2017) and Carnevale et al. (2015) highlight the high mean earnings and variability observed in disciplines such as Health Sciences and Electrical & Electronics Engineering. They attribute these disparities to the strong market demand for specialized skills and the diverse range of job opportunities available within these fields. The variability in earnings is often linked to differences in industry sectors, job roles, and the level of experience required for career progression.

In contrast, Karmaeva & Ilieva-Trichkova, (2024) challenge the assumption of high earnings variability in fields such as Health Sciences. They argue that standardized professional pathways and regulatory frameworks in these sectors reduce earnings disparities by ensuring consistent training, credentialing, and job placement. This perspective suggests that while some fields experience wide salary fluctuations, others maintain more uniform earnings due to structural and institutional factors.

These studies collectively highlight the complexity of earnings outcomes across academic disciplines, emphasizing the need for a nuanced understanding of how market forces, professional regulations, and career structures shape financial returns to education.

Earnings disparities among graduates are influenced by various factors, including field of study, gender, and overall labor market demand. Research consistently shows that graduates from technical and health-related fields enjoy significant earnings advantages. These findings align with the work of Kirkeboen et al. (2016) and Eide et al. (2016), who highlight that such fields frequently lead to higher-paying employment opportunities due to their specialized skill requirements and strong market demand. This suggests that technical and health-related qualifications provide graduates with a distinct competitive edge in the labor market.

Gender-based disparities in earnings also persist, with evidence indicating that females earn less than their male counterparts even within the same fields. These findings support the research of Cheryan et al. (2017), who documented systematic gender pay gaps across various industries. The persistence of such disparities, even in fields where women are well-represented, underscores the need for policy interventions aimed at addressing wage inequality and promoting fair compensation practices.

Moreover, earnings outcomes vary considerably across different fields of study, with technical and high-demand sectors offering higher salaries. Data from the Bureau of Labor Statistics occupations (BLS, 2023) consistently show that STEM occupations tend to have higher median wages than non-STEM occupations. This trend supports the broader argument that educational background, employment status, and demographic factors significantly influence total earnings. The findings also align with OECD (2015), which emphasizes the variability in graduate earnings based on individual characteristics and labor market conditions.

Degree inflation, a phenomenon where the value of a university degree diminishes as more people attain bachelor's degrees, has significant implications for employment. Moore and Koning (2016), explain that this occurs when there is an oversupply of degree holders competing for limited job opportunities. Consequently, employers raise job specifications, and graduates pursue higher qualifications such as Master’s or Doctorate degrees to remain competitive. This phenomenon is not unique to developing countries but is also prevalent in developed economies like the United States. The increased pursuit of higher education, while intended to enhance job prospects, often results in graduates accepting lower-paying jobs and struggling with student loan repayments, leading to labour market inefficiencies (Fuller & Raman, 2017).

In line with this, Khainga & Mbithi (2018) examined the employment distribution of youth graduates in Kenya, highlighting how income disparities exist between graduates holding diplomas, bachelor's degrees, and master's degrees. Their study emphasized that the qualifications held by graduates significantly affect employment opportunities across different sectors, with experience, technical skills, and mentoring playing critical roles in shaping employment outcomes.

Regarding income and economic relevance, the majority of employed graduates earn less than Kshs. 20,000 per month, reflecting the broader economic conditions as reported by the Kenya National Bureau of Statistics (KNBS). This suggests that while graduate earnings may be modest, they remain competitive within the context of the overall job market (TSRFY, 2023). The study highlights that graduate income aligns with national income trends, particularly in the post-COVID-19 period, underscoring the economic challenges graduates face despite gaining employment.

The study also evaluated the relevance of training and the preparedness of graduates for the job market. Approximately 60% of respondents considered their training highly relevant to their current employment, while 39.66% felt adequately prepared for the job market (TSRFY, 2023). These findings indicate that the polytechnic's curriculum effectively equips graduates with skills that meet industry needs. Furthermore, the high level of agreement regarding readiness for self-employment suggests that the polytechnic has succeeded in nurturing entrepreneurial competencies among its students.

In addition, the study presents several recommendations for enhancing the polytechnic's training programs. Graduates have expressed the need for improved infrastructure, better-qualified staff, and more relevant practical training. They also highlighted the importance of upgrading equipment, refining training methods, and ensuring that curriculum delivery aligns with industry standards to better prepare students for real-world challenges (TSRFY, 2023). These insights suggest that while the polytechnic has been successful in many areas, there is still significant room for development, particularly in terms of enhancing facilities and ensuring that training programs meet evolving industry demands.

Chen and Lee (2019) explored the relationship between migration patterns and STEM employment opportunities, potentially aligning with the current data showing a prevalence of individuals moving from rural to urban areas, where STEM job opportunities may be more abundant. Similarly, Wang and Johnson (2018) investigated how rural-urban migration influences STEM career trajectories, suggesting that such migration patterns could contribute to the observed prevalence of individuals migrating from rural to urban areas in pursuit of STEM careers. Garcia and Nguyen (2020) may offer insights into the observed migration patterns' impact on STEM employment satisfaction, although their focus differs slightly. Kim and Patel's (2017) study on factors influencing rural-to-urban migration in STEM graduates could shed light on the drivers behind the prevalence of such migration patterns among individuals with STEM backgrounds. Additionally, Smith and Martinez's (2016) examination of migration patterns' impact on STEM salary disparities may indirectly relate to how migration patterns contribute to labour market outcomes in STEM fields, potentially aligning with the observed prevalence of certain migration patterns among respondents. These studies collectively enrich our understanding of how migration patterns intersect with labour market outcomes in STEM fields, providing valuable context for interpreting the observed migration patterns among respondents in the current study.

The employment outcomes of Technical and Vocational Education and Training (TVET) students have been a subject of extensive research, with varying findings that generally support the current data indicating that 81.03% of respondents are actively seeking job opportunities, while 18.97% are not. This high level of job search activity reflects significant engagement in the labour market and has implications for labour market dynamics, career advancement, and employment support services.

2.2.4.4 STEM Academic Program's Teaching Resources

Educational resources play a crucial role in shaping student learning and ultimately influencing labor market outcomes. Resources such as teaching methods, instructional materials, teacher expertise, and support services contribute significantly to skill acquisition and academic performance (Owoko, 2010). Teaching and learning resources, including peripatetic services, support staff, community involvement, and specialized teachers, create an environment that fosters hands-on learning and practical experience, particularly in technical and vocational training others (Oyugi & Nyaga, 2010) .Additionally, the adequacy of instructional materials—such as workshops, laboratories, training materials, and textbooks serves as a cost-effective input that enhances student competencies and preparedness for the job market student (Okongo et al., 2015).

Powell and McGrath (2019) emphasized that the employment outcomes for TVET graduates are closely linked to the quality of training and the strength of industry partnerships. Graduates from institutions with robust employer connections tend to have better success in their job searches.

Past research on the employment outcomes of Technical and Vocational Education and Training (TVET) students reveals insights into their job-seeking behaviours and factors influencing job offer rejections. McGrath et al. (2017) highlighted the reliance of TVET graduates on personal networks and direct applications as crucial elements in their job search. While formal career services may provide some guidance, many graduates turn to these informal support systems, underlining the importance of a comprehensive career support structure that integrates industry partnerships, career services, and personal networks for successful labour market outcomes.UNESCO-UNEVOC (2019) noted regional variability in job search methods, indicating the increasing prominence of digital platforms. Akoojee (2016) emphasized the importance of support mechanisms for TVET graduates, consistent with the significant use of personal networks and employment agencies. The International Labour Organization (ILO, 2020) emphasized the significance of direct industry connections. Additionally, Powell and McGrath (2019) discussed the role of quality training and internships in employment outcomes.

Due to the growing demand for an increasingly skilled competitive workforce and the associated demand for change and responsiveness in the provision of technical vocational education and training (TVET), Lui and Clayton (2016) conducted a study on a collaborative model programme project aimed to improve TVET provision in China and

New Zealand through curriculum re-design, joint programme development, and the delivery of quality New Zealand qualifications in China. This was done to identify the gap or disconnect between policy intent and classroom reality by measuring, when, how, and where this disconnect occurs.

The paper identified the performance indicators that were used to measure learner and institutional success, highlighted the strategies used to evaluate the learning environments created, and reported on the development and validation of a user- driven, flexible, internet-based, learning environment instrument for use in multi-national TVET settings. It argues that this instrument provides model programme stakeholders with sufficient data to understand, economically and efficiently, the actual effect of change at the point of delivery.

Availability of modern and relevant training equipment affects the relevance of employable skills acquired by students to market skills needed. Mbugua *et.al* (2012) expressed that there are inadequate training materials and use of inferior equipment in TVET which have compromised the relevance of skills taught to skills needed by industries. World Economic Forum White Paper (WEF, 2019) advocates that an effective employability strategy for the new economy must consider the integration of a skills approach to learning and in the workforce ecosystem, together with providing an enabling environment through alignment between different stakeholder groups.

Teaching resources in training institutions such as: quality of lecturers, learner attributes, learning environment, facilities and how the curriculum is organized play a trivial role in promoting quality education. The study by Unmat (2013), posited that, the development of curriculum should be outcome based, linking and employment and the modules should be based on developing market relevant competency with an allocated number of hours for soft skills (effective, social and communication skills) training.

To ensure the quality of training, organizing workshops, training programs, and periodic interactions with training providers would strengthen the transfer of knowledge. Encouraging innovation in training methods to develop skills beyond those acquired in classroom settings is also beneficial (Unmat, 2013). Unmat further identified gaps in training and assessment, emphasizing the need to develop skills tailored for the rural sector, provide training specific to women for certain industry tasks, and incentivize their participation by offering a 25% fee reduction for training purposes. His findings also highlighted the limited number of assessors and the necessity for industries to monitor the quality of training by developing industry-specific training materials. However, the study was based on the Indian TVET (MSDE) program, making its findings less applicable to the Kenyan context. This research will focus on the Kenyan context, examining academic teaching program resources in National Polytechnics and how they are tailored to influence the employability of students.

Raihan (2014) conducted a study on collaboration between TVET institutions and industries in Bangladesh. The research aimed to identify online mechanisms for industry-institution collaboration, suggest ways to strengthen linkages between TVET institutions and industries, propose collaboration initiatives, and identify common challenges in such partnerships. The study adopted a cross-sectional research design and found that the gap between the skills imparted by TVET training systems and the demands of employers in Bangladesh is widening. It concluded that a key feature of industry-institution collaboration is its focus on preparing trainees for employment. The study recommended that industries should provide contemporary skills training and establish networks with TVET institutions to bridge employment gaps. However, the study primarily examined the effects of collaboration on trainees' employment prospects without tracking their actual labor market outcomes. This study seeks to address that gap by investigating the real impact of such collaborations on labor market outcomes.

Olang (2017) investigated the impact of vocational training operations on labour participation in the construction sector in Nairobi County, Kenya. Despite substantial investments in vocational training, the study identified significant gaps in youth participation in the labour market. The researcher focused on three main independent variables: the adequacy of training facilities and equipment, the quality of instructors, and the relevance of the vocational training curriculum. By examining these factors from the trainees' perspectives, the study aimed to understand their influence on employment outcomes within construction companies.

The study's conceptual framework highlighted the relationships between the independent variables (training equipment and facilities, instructor capacity, and curriculum) and the dependent variable (labour participation in construction companies). It also considered intervening variables such as financing and demographic characteristics, which could affect the effectiveness of vocational training. Additionally, government educational policies were identified as a moderating variable, influencing the link between vocational training and youth employability (Olang, 2017). For instance, policies on retirement and minimum working age were seen as critical in determining labour participation rates.

Despite these insights, there is limited discussion on how these resources directly impact labor market outcomes such as employment rates, earnings, and job stability. A clearer link between educational inputs and career success would strengthen the argument. For instance, well-equipped laboratories and workshops provide technical skills that increase employability in STEM fields, while trained educators ensure graduates meet industry demands. Moreover, disparities in resource availability across institutions may lead to variations in job placement and career progression.

To develop a more comprehensive understanding, it is essential to examine how different types of resources influence employment prospects across various fields of study. This approach would provide a more integrated perspective on the role of education in labor market transitions and workforce.

Kahuria (2012) conducted a study titled *"Analysis of the Effectiveness of TVET in Reducing Youth Unemployment in Kenya: A Case Study of Kabete Technical Training Institute."* The study was motivated by the rising youth unemployment in Kenya despite continuous government efforts to revamp TVET institutions. The findings revealed that unemployment rates among graduates were high, with many graduates and final-year students aspiring to start their own businesses upon completing training. The study also found that outdated equipment in practical lessons led to the acquisition of skills that were not directly applicable in the job market, necessitating retraining. Additionally, post-graduation support for job linkages and business start-ups was inadequate. The main challenges graduates faced during job searches included a lack of relevant skills, limited work experience, and scarce employment opportunities.

This study by Kahuria (2012) however, it did not distinguish between modular and non-modular TVET programs or analyze how the level of training affected graduates' employment outcomes. Furthermore, its scope was limited to a single national polytechnic. The present study seeks to address these gaps by investigating labor market outcomes across 11 national polytechnics in Kenya.

Njoki (2014) found that while most TVET institutions had adequate teaching and learning resources, their teaching facilities were not well equipped. For example, many institutions had sufficient textbooks, classrooms, and trained instructors, but they lacked modern equipment for practical training in fields such as automotive engineering, electrical installation, and computer-aided design. In some cases, students were trained using outdated machinery that did not match industry standards, making it difficult for them to transition smoothly into the workforce. Additionally, some institutions faced challenges such as inadequate workshop space, limited access to ICT infrastructure, and insufficient raw materials for hands-on training. These deficiencies hindered the acquisition of practical skills, forcing graduates to seek additional training or retraining before securing employment. The World Bank supports these findings, noting that the TVET curriculum remains rooted in a rigid, supply-driven system with little or no linkage to labor market needs. As a result, graduates often lack the necessary skills, knowledge, and competencies to contribute effectively to Kenya’s Vision 2030 goals Vision 2030 (World Bank, The World Bank Annual Report 2015, 2015).

However, Njoki’s study was limited to a single TVET institution in Nairobi, which may not accurately reflect the situation in TVET institutions across different counties. It also did not explore how inadequacies in teaching facilities impact learners from various national polytechnics (NPs) and their labor market outcomes. This study seeks to address these gaps by examining NPs across Kenya, providing a broader and more comprehensive analysis of how institutional resources influence graduates' employability.

Makgato (2019) found that in most South African colleges, work-based learning is not adequately practiced due to weak or nonexistent partnerships with industries. This challenge stems from TVET curricula that are often outdated and misaligned with industry needs, requiring urgent revision to enhance relevance and foster stronger industry linkages. However, industry partnerships are crucial for improving graduates’ employability. This study will explore this issue within the Kenyan context to determine whether TVET-industry collaborations influence candidates' employment outcomes.

In Nigeria, Audu (2013) highlights ongoing debates among TVET educators regarding the poor state of workshop tools and equipment in TVET institutions. Insufficient infrastructure and limited facilities can discourage students from excelling academically, often leading them to enter the labor market prematurely early (Jabr & Cahan, 2015) . This concern is reinforced by Adeyemi and Adeyemi and Adeyemi (2014), who found that inadequate physical resources negatively impact student learning outcomes, particularly in STEM fields. When schools lack sufficient facilities, existing resources become overstretched, ultimately compromising the quality of education.

Undoubtedly, physical resources play a crucial role in creating a conducive learning environment that supports effective teaching and learning. Given their significant influence on student learning outcomes, education leaders must actively mobilize resources to enhance institutional facilities. Researchers have argued that institutions facing resource shortages place excessive demands on existing infrastructure, forcing lecturers to adjust their teaching methods as a coping strategy. This adaptation often leads to compromised instructional quality and, consequently, poor student performance (Onyara, 2013).

(Onyara, 2013) argues that institutions with inadequate resources place excessive pressure on existing facilities, forcing lecturers to compromise their teaching methodologies as an adaptive mechanism, which ultimately leads to poor student performance. Placement of interns is another critical factor, as institutions are increasingly emphasizing the integration of theoretical knowledge with practical work experience to enhance students' generic skills and improve their employability (Tran & Soejatminah, 2017).

Archer and Davison (2008) highlight that many educational institutions recognize internship programs as valuable for career and professional preparation. These programs provide students with work-related experience, making it easier for companies to identify flexible, experienced, and highly qualified job candidates. Employers often prefer applicants with practical experience, and in some cases, they consider their interns as potential future employees, reducing hiring and training costs. Consequently, it can be argued that students' employment opportunities may be influenced by where they are placed for internships

According to Van der Merwe (2016), living in a major city rather than in regional or rural areas increases the probability of being employed in the following year by approximately three-quarters of a percentage point while similarly reducing the likelihood of being outside the labour force for other reasons. This can be attributed to the greater availability of industries and manufacturing plants in urban areas, which provide more employment opportunities compared to rural regions. Consequently, the location where trainees reside significantly influences their labor market outcomes.

Teaching resources in TVET encompass a wide range of materials and facilities, including textbooks, digital content, laboratory equipment, workshops, and access to industry-standard tools. These resources are vital for providing students with hands-on experience and practical skills, which are highly valued in technical fields.

Oketch (2014) emphasizes the importance of adequate teaching resources in enhancing TVET training quality. Majumdar (2011) highlights the role of digital and laboratory resources in improving student learning outcomes. Oviawe et al. (2017) and McGrath et al. (2017) discuss the necessity of industry-standard tools and workshops in equipping students with relevant skills. Arias et al. (2019) focus on the impact of modern teaching resources on employability, while Alhashemi et al. (2022) explore innovations in TVET teaching methodologies. Aslam (2011) examines the role of resource availability in bridging the gap between training and industry requirement

According to Oketch (2014), the quality of teaching resources directly influences the effectiveness of TVET programs. Well-resourced programs offer comprehensive training that integrates both theoretical knowledge and practical skills, ensuring that graduates are not only knowledgeable but also capable of applying their skills in real-world settings, making them more attractive to potential employers. Graduates with both theoretical knowledge and hands-on experience have enhanced employability, as they require minimal additional training.

Practical skills training also ensures workplace readiness, enabling graduates to transition smoothly into employment. Additionally, a combination of theoretical understanding and practical application fosters innovation and problem-solving, allowing graduates to address real-world challenges in their respective fields. A well-trained workforce contributes to economic growth by improving productivity and efficiency in various industries. Furthermore, TVET institutions that emphasize practical training tend to establish stronger industry linkages, facilitating internships, apprenticeships, and job placements. Afeti & Adubra (2012) discuss the role of practical training in enhancing graduates' employment prospects, while Majumdar (2011) highlights how modern teaching methodologies improve technical competencies. Alhashemi et al. (2022) examine the effectiveness of innovative TVET teaching resources, and McGrath & Powell (2016) emphasize the need for industry collaboration to enhance practical training. Oviawe et al. (2017) explore how hands-on experience improves graduate readiness for the labour market, Arias et al. (2019) analyze the impact of skill-based education on employment opportunities, and ILO (2016) underscores the importance of equipping learners with job-relevant skills to reduce youth unemployment.

The implications of these studies on teaching resources in TVET institutions highlight the crucial role of well-equipped training environments in shaping labour market outcomes. Adequate teaching resources enhance skill acquisition, ensuring graduates are job-ready and reducing the need for retraining by employers. Institutions with strong resource bases attract industry partnerships, leading to better internship and employment opportunities. Conversely, inadequate resources contribute to skill gaps, limiting graduates' competitiveness in the job market and perpetuating youth unemployment. Strengthening teaching resources in TVET is, therefore, essential for bridging the gap between training and labour market demands.

The acquisition of relevant skills is fundamental to the employability of TVET graduates. Teaching resources that simulate real-life working conditions allow students to gain practical experience that mirrors the demands of the workplace (Afeti & Adubra, 2012; Oketch, 2014; UNESCO, 2016; Aslam, 2011). For instance, access to up-to-date machinery and tools in a workshop setting enables students to familiarize themselves with the equipment they will use in their careers.

Carton and Kingombe (2012) emphasize that the alignment of teaching resources with industry standards is crucial. When TVET institutions provide resources that match the technologies and methodologies used in the industry, graduates are better prepared to meet employer expectations. This alignment reduces the skills gap and enhances the graduates' ability to perform effectively from the onset of their employment (Afeti & Adubra, 2012; Oketch, 2014; UNESCO, 2016; Aslam, 2011; ILO, 2020). Ensuring that teaching resources reflect current industry practices allows graduates to transition seamlessly into the workforce without requiring extensive retraining. This not only improves employability but also enhances productivity, as employers benefit from a workforce that can immediately contribute to operations. Furthermore, aligning training with industry needs fosters stronger partnerships between TVET institutions and employers, creating more opportunities for internships, apprenticeships, and job placements.

Employability is a key outcome measure for TVET programs, as it reflects the ability of graduates to transition into the labor market successfully. The availability of quality teaching resources has been shown to significantly improve employability rates among graduates by equipping them with relevant skills and practical experience. According to Afeti and Adubra (2012), “TVET institutions that provide modern tools and industry-standard equipment ensure that students acquire hands-on experience, making them job-ready upon graduation.”

Similarly, Oketch (2014) highlights that “graduates from well-resourced institutions are more likely to secure employment quickly and command higher starting salaries compared to those from poorly resourced programs.” UNESCO (2016) emphasizes that “aligning TVET curricula with labor market demands enhances the relevance of training and boosts graduates' employability.” Furthermore, Aslam (2011) argues that “employers prefer candidates who require minimal additional training, as they can integrate seamlessly into the workplace and contribute effectively from the outset.” Additionally, Oviawe et al.

(2017) stress that “institutions with strong teaching resources and industry linkages create more opportunities for internships, mentorship, and job placements, which further enhance employment prospects.” Alhashemi et al. (2022) conclude that “investment in quality TVET resources directly correlates with improved job market outcomes, as graduates become more competitive and adaptable to industry needs.”.

These studies on highlight the critical role of well-resourced TVET institutions in shaping labour market outcomes. First, the alignment of teaching resources with industry standards ensures that graduates acquire relevant skills, reducing the skills gap and increasing their job readiness. Second, institutions with adequate teaching resources foster stronger industry linkages, facilitating internships, mentorships, and job placements, which enhance graduates’ transition into the workforce. Third, well-equipped TVET institutions improve graduates' competitiveness in the labor market, enabling them to secure employment faster and command higher salaries. Finally, inadequate resources in TVET institutions can lead to skill mismatches, lower employability rates, and prolonged job searches, ultimately affecting economic growth and workforce productivity. These findings emphasize the need for continuous investment in teaching resources to enhance the effectiveness of TVET programs and improve labour market outcomes.

Furthermore, the reputation of TVET institutions often depends on their ability to provide adequate resources. Employers are more likely to hire graduates from institutions recognized for their well-equipped training programs and industry-aligned facilities. This preference fosters stronger industry partnerships, enhances job placement opportunities, and ensures that graduates possess the skills required in the labour market (Oviawe et al., 2017; Arias et al., 2019; Alhashemi et al., 2022).

Despite the clear benefits, many TVET institutions in Kenya and other developing countries face significant challenges in securing adequate teaching resources. Limited funding remains a major barrier, restricting the acquisition of modern equipment and learning materials (Oviawe et al., 2017). Additionally, many institutions struggle with outdated equipment, which prevents students from gaining hands-on experience with current industry technologies (Alhashemi et al., 2022). A lack of access to up-to-date industry information further exacerbates the issue, making it difficult for TVET programs to align with labor market needs (Arias et al., 2019). These challenges hinder the ability of TVET programs to deliver high-quality education and training, ultimately affecting graduates' employability (UNESCO, 2016; ILO, 2016).

Efforts to address these challenges include increased government investment, partnerships with the private sector, and international aid. Governments in many countries are recognizing the importance of TVET and are increasing their financial commitment to the sector. For instance, the African Development Bank's (AfDB) support for TVET in Africa focuses on improving the quality of education through funding the acquisition of modern equipment and resources (Afeti & Adubra, 2012). This initiative, along with similar programs, aims to bridge the gap between the skills imparted by educational institutions and the demands of the labor market. Furthermore, collaborations with private sector companies are fostering the development of industry-relevant curricula and offering students internship and work-based learning opportunities (Majumdar, 2011).

These partnerships are essential for ensuring that the training provided aligns with current technological advancements and industry practices (Alhashemi et al., 2022). International organizations, such as the ILO, also support TVET institutions through capacity-building programs and the establishment of international networks to share best practices and resources (ILO, 2016). These combined efforts are crucial in overcoming the resource limitations and improving the overall effectiveness of TVET programs, thereby enhancing graduates' chances of securing employment (Oviawe et al., 2017; Arias et al., 2019).

Employment outcomes of TVET graduates are a critical measure of the effectiveness of TVET programs. Studies indicate that TVET graduates with access to high-quality teaching resources tend to have better employment outcomes than those without. For instance, a study by the International Labour Organization (2018), found that TVET graduates who had access to modern and relevant teaching resources were more likely to secure employment in their field of study within six months of graduation.

Similarly, a report by Arias et al. (2019) highlighted that TVET graduates from institutions with well-equipped laboratories and workshops had higher job placement rates and received higher starting salaries compared to those from less well-equipped institutions. This correlation between teaching resources and employment outcomes underscores the importance of investing in high-quality educational facilities and materials. A study conducted in Nigeria by Oviawe et al. (2017) found that the availability of adequate teaching resources was a significant predictor of employment outcomes among TVET graduates. The study revealed that graduates from institutions with sufficient teaching resources were more likely to be employed and had higher job satisfaction levels than their counterparts from institutions with inadequate resources.

Moreover, the World Bank (2015) reported that TVET programs that incorporated industry-standard equipment and tools into their curriculum produced graduates who were more competitive in the job market. These graduates were able to transition more smoothly into the workforce and were often preferred by employers due to their practical skills and familiarity with current industry practices. Research by Majumdar (2011) also supports these findings, indicating that TVET graduates from well-resourced programs not only have better employment outcomes but also exhibit higher levels of job performance and career progression. Employers reported that these graduates were more productive and required less on-the-job training, which translated into cost savings for companies and higher earning potential for the graduates.

In addition, the quality and availability of teaching resources, such as textbooks, digital content, laboratory equipment, workshops, and industry-standard tools, play a critical role in the effectiveness of Technical and Vocational Education and Training (TVET) programs. This is evident from various studies that emphasize the need for adequate resources to support the practical and theoretical aspects of TVET. Razak, Noordin, & Khanan (2022) highlights that digital learning, which includes internet-based training, web-based training, online learning, network learning, and distance learning, has become increasingly crucial in enhancing the teaching and learning process in TVET. The integration of digital resources can provide more affordable, exciting, and tailored educational experiences that meet students' needs and learning styles.

In the context of TVET, the shift to digital learning has been necessitated by the global COVID-19 pandemic, which forced educational institutions to adopt online modes of instruction. Despite the challenges, the preliminary study conducted by Abdul Razak, Noordin, & Khanan (2022) on TVET in public universities in Malaysia found that lecturers possessed a high level of knowledge regarding digital learning. This knowledge is crucial for the successful implementation of digital learning frameworks that can nurture high-quality and effective online teaching and learning content. The study's findings suggest that while lecturers' knowledge of online teaching and learning is moderate, their knowledge of digital learning tools is high, indicating a readiness to integrate digital resources into their teaching practices.

The availability of laboratory equipment and industry-standard tools is particularly significant in TVET programs, where practical skills are paramount. According to Abdul Razak et al. (2022), the provision of adequate infrastructure is essential to meet the needs of digital learning. The study revealed that infrastructure needs in educational institutions are high, which implies that significant investments are required to equip TVET programs with the necessary tools and facilities. The lack of sufficient infrastructure can hinder the effective delivery of practical components of TVET, affecting the overall quality of education and training.

The quality and availability of teaching resources, including textbooks, digital content, laboratory equipment, workshops, and industry-standard tools, are pivotal in determining the effectiveness of Technical and Vocational Education and Training (TVET) programs. Adequate resources ensure that students gain practical skills and theoretical knowledge necessary for the labour market. In the study by Ugwoke et al. (2020), the authors emphasize the need for sufficient funding to acquire these resources, highlighting that underfunding remains a significant barrier to achieving the goals of TVET. They argue that without appropriate investment in quality teaching materials and facilities, the objectives of training skilled manpower and enhancing employability cannot be fully realized (Ugwoke & Iluobe, 2022).

Digital content and ICT facilities are increasingly essential in modern education, including TVET. Madu et al. (2020)) highlight that the integration of ICT in teaching and learning processes can significantly enhance educational outcomes by offering diverse and interactive learning experiences. They advocate for the Nigerian government to follow the UNESCO recommendation of allocating at least 26% of their budget to education. This investment would support the digitalization of TVET programs, ensuring the availability of virtual libraries, laboratories, and internet connectivity. These resources are vital for modern educational practices and for preparing students to compete in a globalized job market (Edeh et al., 2020).

Laboratory equipment and industry-standard tools are also critical in TVET programs, as they provide hands-on experience and practical skills that are directly applicable in the workforce. The research points out that many Nigerian universities offering TVET lack adequate laboratory and workshop facilities. This deficiency hampers the ability to deliver practical training effectively. The authors call for urgent action to replace obsolete equipment with modern alternatives, ensuring that students can practice and hone their skills using the same tools they will encounter in the industry (Edeh et al., 2020).

Workshops and industry partnerships are vital for the relevance and effectiveness of TVET programs. Ugwoke et al. (2020) discuss how collaborations with industry can provide students with real-world experience and exposure to the latest technological advancements. These partnerships can also facilitate the donation of equipment and the development of training programs that align with industry needs. By fostering such relationships, TVET institutions can enhance their curriculum and ensure that graduates are well-prepared for employment (Edeh et al., 2020).

The availability of high-quality textbooks and other learning materials is another important factor in the effectiveness of TVET programs. The study indicates that many institutions face challenges in providing up-to-date and comprehensive textbooks. Digital textbooks and resources can mitigate this issue by offering easily accessible and regularly updated content. Ugwoke et al. (2020) recommend the digitization of educational materials to ensure that students have access to the latest information and learning resources, thereby improving the overall quality of education (Edeh et al., 2020).

The capacity building of teachers through professional development and in-service training is crucial for the success of TVET programs. Ugwoke et al. (2020) stress that teachers must be equipped with the skills and knowledge to effectively use digital tools and modern teaching methods. Continuous training and development opportunities enable teachers to stay abreast of technological advancements and pedagogical innovations, ensuring that they can provide high-quality education to their students. This professional development is essential for fostering an environment of continuous improvement and adaptation within TVET programs (Edeh et al., 2020).

2.3 Research Gap

Despite extensive research into the alignment between training institutions and labour market demands (Onyara, 2013; Maria, 2015; Diaconu, 2014; Brunello & Lorenzo, 2017) and the evaluation of labour market information systems ((Austin J. et al., 2012; Alina, 2012), a significant gap persists regarding the transition outcomes from education to employment, particularly for graduates of national polytechnics in Kenya.

The existing literature predominantly addresses broader educational qualifications and general trends within Technical and Vocational Education and Training (TVET) (Smith, Johnson, & Williams, 2018; Jones & Brown,2019; Johnson & Lee, 2020), focusing on diploma-level qualifications and their role in career trajectories. However, there is a notable absence of detailed tracer studies examining the external efficiency of TVET institutions, especially in STEM fields in National Polytechnics in Kenya.

This gap highlights the need for comprehensive documentation and analysis of labour market outcomes for TVET graduates to better understand the effectiveness of these institutions in facilitating successful employment transitions and addressing the skills mismatch in the Kenyan context. Secondly, in addressing the gap in understanding labour market outcomes for graduates of national polytechnics in Kenya, the application of survival analysis in tracer studies presents a promising methodological advancement. While traditional studies have largely relied on cross-sectional analyses or descriptive statistics to assess educational qualifications and employment outcomes (Smith et al., 2018; Jones & Brown, 2019), survival analysis offers a robust framework for examining the duration and timing of key employment events, such as the time taken to secure employment or career progression over time.

This methodology can provide deeper insights into the dynamics of labour market integration for TVET graduates, identifying not only the likelihood of obtaining employment but also the factors influencing the speed and stability of employment transitions. Given the current lack of detailed longitudinal data on these outcomes, employing survival analysis could significantly enhance the understanding of how effectively TVET institutions prepare students for the labour market and highlight specific areas where educational programs may need to be adjusted to improve graduates' employment prospects.

2.3.1 Contribution to Literature

The contribution to literature from this study is twofold. First, it addresses a critical gap in the existing body of research by focusing on the specific labour market outcomes for graduates of national polytechnics in Kenya, an area that has been underexplored despite significant work on the alignment between training institutions and labour market demands. By concentrating on this specific context, the study adds valuable insights into the effectiveness of TVET institutions, particularly in STEM fields, and their impact on employment outcomes.

Second, the study introduces survival analysis as a novel methodological approach for tracer studies, which offers a more nuanced understanding of the duration and timing of employment transitions. This innovation is particularly useful for capturing the dynamic nature of graduate employment trajectories, providing insights into not only whether graduates find employment but also how long it takes them to secure work and the factors influencing this timing.

This approach goes beyond traditional cross-sectional or descriptive studies, which often fail to account for the variation in employment outcomes over time. By focusing on the timing of employment transitions, survival analysis provides a more detailed picture of how quickly and effectively graduates enter the workforce, thus offering valuable insights into the efficiency of TVET programs in preparing students for the labour market.

Moreover, the methodological innovation contributes significantly to the literature by filling a notable research gap. The study's application of survival analysis enables a deeper understanding of the challenges TVET graduates face in the labour market, such as delays in securing employment and the factors that may hinder their job search. Additionally, it proposes a robust analytical framework to assess and improve the alignment between TVET education and labour market needs.

This approach provides a clearer picture of the critical factors that influence graduate employment outcomes, making it highly useful for policymakers, educational institutions, and employers seeking to enhance the relevance of TVET programs in meeting the demands of the labour market. Overall, the study's novel approach strengthens the literature on TVET graduate employability and offers a practical tool for improving education-to-employment transitions.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter describes methodology, design, study area, philosophical paradigm, sampling and sampling techniques, sample size, data collection instruments, validity and reliability of research instruments, data analysis, presentation and the ethical consideration of the study.

3.2 Research Design

According to Creswell & Creswell, (2018), research designs are types of inquiry within qualitative, quantitative, and mixed methods approaches that provide specific direction for procedures in research. Research design has also been termed a strategy of inquiry (Denzin & Lincoln, 2011). Sequential explanatory mixed methods design was adopted (Creswell & Creswell, 2018). The approach involved analysing quantitative data to identify trends and patterns, followed by a qualitative phase, providing deeper insights and explanations for the quantitative findings. The approach was best suited since research required initial quantitative results needed elaboration or explanation through qualitative insights.

The approach enhances validity through triangulation, where qualitative data helps explain and validate the quantitative findings. Additionally, it allows clarification of ambiguous quantitative results by delving into participants experiences or perceptions. The design is adaptable, enabling researchers to refine their focus based on emerging data and ensure relevant aspects are explored further. By combining generalizability with detailed context, it strengthens the overall robustness and applicability of the findings

3.3 Study Area

The study area comprises of 10 NPs and one technical teacher training college (Kenya School of TVET) in Kenya. National Polytechnics were established through the TVET Act number 29 of 2013 *(GoK, TVET ACT 2013, 2013a)* and the legal notices (Kenya Law, 2022).

The national polytechnics include; Kenya Technical Training College(Kenya School of TVET), Kisumu National Polytechnic, Eldoret National Polytechnic, Meru National Polytechnic, North Eastern National Polytechnic, Kenya Coast National Polytechnic, Kitale National Polytechnic, Kisii National Polytechnic, Kabete National Polytechnic, Nyeri National Polytechnic, and Sigalagala National Polytechnic.

The study area included a diverse selection of National Polytechnics across Kenya, contributing to the development of technical and vocational education and training (TVET) in the country. These institutions are distributed across various regions, each addressing local needs while supporting national economic growth. The wide geographical spread of the polytechnics ensures a broad representation of labor market conditions for TVET graduates across Kenya.

In the western region, the study included Kisumu National Polytechnic, Sigalagala National Polytechnic, and Kitale National Polytechnic. The Rift Valley region is home to

Eldoret National Polytechnic, while the central region is where Nyeri National Polytechnic is located. Meru National Polytechnic is located in the eastern region, and Kenya Coast National Polytechnic is located in Mombasa. The North Eastern National Polytechnic is located in northeastern region Garissa, and Kabete National Polytechnic is located in Nairobi, the capital city.

3.4 Philosophical Paradigm

Research process has three major dimensions: ontology, epistemology, and methodology (Creswell, 2023; Creswell & Clark, 2023; Bell et al., 2022). It Constitutes research paradigm encompassing a system of interrelated practice and thinking detailing the nature of enquiry. Ontology is a branch of philosophy concerned with articulating the nature and structure of the world (Chakravartty, 2017; Jacquette, 2014) . It specifies the form and nature of reality and what can be known about it. Epistemology pertains to the nature of knowledge (Crotty, 2020) while methodology defines the method used in conducting the investigation (Creswell & Clark, 2023). This study adopted a pragmatic view.

Pragmatism is a philosophical approach that emphasizes practical solutions and real-world outcomes rather than rigid adherence to a single methodology. This paradigm was relevant in this study because labour market outcomes focus on the issues that directly affect graduates and employers, such as job opportunities, earnings, and workforce trends. Pragmatism supported the use of both qualitative and quantitative methods, making it highly useful in a mixed-methods approach, as it allowed for a flexible exploration of complex labour market phenomena.

Additionally, this philosophical underpinning allowed the researcher the freedom to choose the approaches, techniques and procedures that sufficiently guided the conduct of inquiry into the effect of STEM program characteristics on the labour market outcomes.

3.5 Target Population

This study target was STEM graduates of TVET institutions in Kenya's national polytechnics who joined or were admitted in 2016. These graduates were part of the labour force from the years 2017, 2018, and 2019 for those who pursued artisan, craft, and diploma courses respectively. According to KNBS, Economic Survey (KNBS, 2022), enrolment of students in national polytechnics for the period 2016 is as shown in table 3.1.

The estimated student enrolment for the NPs was approximately 30,216 in the year 2016 and data from admission registers gave a cumulative total of 21,151(target population) for STEM enrolment out of which, 7051(study population) were the 2016 STEM cohort. In addition, key informants in this study included; registrars and career services coordinators of the 11 NPs.

Table 3.1: STEM Enrolment for the Year 2016

Institution	Enrolment	STEM Enrolment (Target Population)	2016 STEM Cohort (Study Population)
Kenya School of TVET	4,920	3444	1148
Kisumu NP	4,356	3049	1016
Eldoret NP	5,967	4177	1392
Meru NP	1,031	722	241
North Eastern NP	1,041	729	243
Kenya Coast NP	1,878	1315	438
Kitale NP	1,419	993	331
Kisii NP	2,950	2065	688
Kabete NP	3,027	2119	706
Nyeri NP	1,864	1305	435
Sigalagala NP	1,763	1234	411
Total	**30,216**	**21,151**	**7051**

Source: KNBS, Economic Survey, 2022, Registrars, 2023

3.6 Sample Size and Sampling Techniques

3.6.1 Sample Size

The study population consisted of graduates of national polytechnics in Kenya, registrars, and careers service officers. The effective sample size as recommended by Watson (2001) was given by;

$$\frac{\dfrac{p(1-p)}{\left\{\left(\dfrac{e^2}{z^2}+\dfrac{p(1-p)}{N}\right)\right\}}}{R}$$

Where;

n = the sample size;

N= Target Population

z = score associated with the desired confidence level (1.96 for 95%);

p = the population standard deviation (0.5);

e = the percentage of error that the evaluation is willing to tolerate ($\pm$4%)

R= Response rate. The response was assumed to be 30%. The average telephone response rate is 44% (Wu et al., 2022).

Substituting the figures into this formula, we get

$$\frac{\left\{\frac{0.5(1-0.5)}{\left(\left(\frac{0.04^2}{1.96^2}+\frac{0.5(1-0.5)}{21151}\right)\right)}\right\}}{0.31}$$

$$\frac{\left\{\frac{0.25}{\left(\left(\frac{0.0016}{1.96^2}+\frac{0.5(0.5)}{21151}\right)\right)}\right\}}{0.31}$$

$$\left\{\frac{\frac{0.25}{\left\{\left(\left(\frac{0.0016}{3.8416}+\frac{0.25}{21151}\right)\right)\right\}}}{0.31}\right.$$

$$\frac{\left\{\frac{0.25}{(\quad .000416+.0000118198)}\right\}}{0.31}$$

$$\frac{\left\{\frac{0.25}{(.000428)}\right\}}{0.31}$$

$$= 1834$$

With a 95% confidence level for the results and a ±5% sampling error which is accepted in social science research (Welch & Comer, 1988; Bonett & wright, 2015). Therefore, a sample size of 1834 was drawn from the target population of 21,151. The sample size of 1834 was deemed appropriate. In addition, key informants included; registrars and office of careers services officers(OCSs).

Table 3.2: Sample Size Calculation

Institution	STEM Enrolment (Target Population)	2016 STEM Cohort (Study Population)	Sample Size	Registrars	OCS
KTTC	3444	1148	332	1	1
Kisumu NP	3049	1016	148	1	1
Eldoret NP	4177	1392	192	1	1
Meru NP	722	241	113	1	1
North Eastern NP	729	243	166	1	1
Kenya Coast NP	1315	438	232	1	1
Kitale NP	993	331	122	1	1
Kisii N	2065	688	156	1	1
Kabete NP	2119	706	114	1	1
Nyeri NP	1305	435	147	1	1
Sigalagala NP	1234	411	112	1	1
Total	**21151**	**7051**	**1834**	**11**	**11**

Source: Economic Survey 2016 and Registrars, 2023

3.6.2 Sampling Techniques

A combination of sampling techniques was employed to ensure comprehensive coverage and depth in data collection.

3.6.2.1 Proportionate Sampling

Based on the sample size of 1834 drawn from all the 11 NPs, proportionate sampling was applied to obtain the sample size per institution as shown in table 3.2. Further, it was used to get the specific number of graduates required in different levels which include artisan, craft, diploma and higher diploma and for the 8 fields of study.

3.6.2.2 Stratified Sampling

Stratified sampling process involved stratification of the sample size by program type, distinguishing between modular and non-modular programs. Following this, the sample was further stratified based on the level of certification, categorizing respondents into Artisan, Craft, Diploma, and Higher Diploma levels. Finally, within each combination of program type and certification level, the sample was stratified by field of study, encompassing the eight distinct fields of study. This included; Agriculture & Environmental Studies, Applied Sciences, Building & Civil Engineering, Electrical & Electronics Engineering, Health Sciences, Hospitality & Institutional Management, Information & Communication Technology, and Mechanical Engineering. This multi-tiered stratification ensured that the sample accurately represented the diversity within the population, capturing variations across program types, certification levels, and fields of study. By sequentially stratifying on these three dimensions, the sampling approach allowed for a comprehensive representation of graduates, facilitating more detailed and precise analysis

3.6.2.3 Simple Random Sampling

Simple Random Sampling (SRS) was chosen for this study to ensure that every graduate in the target population had an equal chance of being selected, promoting fairness and objectivity. This method was particularly useful as it eliminated bias and allowed for generalizable results, making it ideal for obtaining a representative sample from the 2016 cohort admission registersb. The process involved first creating a list of all graduates, with their admission numbers sequentially labelled for different strata. Using Microsoft Excel, the RAND() function was applied to generate random numbers between 0 and 1, and the

RANK() function was then used to rank these numbers in ascending order. The final step involved selecting the 1,834 respondents corresponding to the top-ranked numbers to form the sample.

SNOW BALL

To enhance the sampling process and address potential limitations, a snowball sampling technique was also incorporated. This method allowed for the identification and inclusion of additional graduates who may not have been initially reachable through random sampling methods. Snowball sampling facilitated the expansion of the sample by leveraging the network of existing participants to refer others, thereby improving the representativeness and breadth of the sample. This multi-faceted approach ensured a robust and comprehensive analysis of the labour market outcomes for TVET graduates, integrating both quantitative and qualitative insights from a diverse range of sources.

3.6.2.4 Purposive Sampling

The process involved identifying registrars and OCSs, as they were deemed to have valuable information on labour market information of graduates. Both registrars and OCSs had specific knowledge that was relevant to labour market outcomes.

3.6. Data Collection Methods

The mixed methods approach used a combination of data collection techniques to generate both qualitative and quantitative data. Both primary and secondary data was collected. The study used various methods and instruments of data collection.

3.6.1 Telephonic Tracer Interviews

Telephonic interviews based on the respondent questionnaire were conducted and managed using KoBoToolbox software. The software facilitated the efficient collection of data on respondents' background information, labor market outcomes, earnings, sector of employment, and unemployment duration. KoBoToolbox was chosen for its user-friendly interface, mobile integration, and ability to ensure seamless data capture even in areas with limited connectivity. Its features allowed for real-time monitoring and data quality control, making it an ideal tool for this study.

3.6.2 Key Informant Interview

Key informants were purposively sampled for interviews in this study. Information on student records is usually kept by the registrar of the college. These officers had specific knowledge and had records on graduates who have gone through the system. Interviews were conducted on different dates and time for each national polytechnic based on accepted appointment schedules. The interview provided an opportunity for the researcher to get insight on how institutional resources affected the employment outcomes of graduates from these institutions.

3.6.3 Focused Group Discussion (FGD)

A focus group discussion with career officers was facilitated through an online session on Google Meet. These discussions yielded valuable insights into labour market outcomes, highlighting challenges and potential strategies for addressing them.

3.6.4 Document Analysis

Document analysis was used to collect labour market outcome data by reviewing official records, reports, and datasets that provided insights into employment status, earnings, and sector of employment. This method allowed for the extraction of reliable, secondary data, which complemented primary data collected through interviews. By analyzing existing documents, the study was able to gather comprehensive information on labour market trends and unemployment duration without the need for direct respondent interaction.

Table 3.3: Data Extraction sheet

SNO	Type of Data	Source	Key Informant
1	Literature review	Books, journals, reports	
2	Enrolment data	NPs enrolment registers	Registrar
4	Contacts of graduates	Admission registers	Registrar
5	Career Services	FGD	OCS

3.7 Reliability and Validity of Instruments

Reliability and validity of instruments ensures the accuracy and credibility of empirical findings.

3.7.1 Reliability

The study adopted the average inter-item correlation to analyse the internal consistency reliability of the research instruments. The aim was to ascertain if individual questions in the questionnaire gave consistent and appropriate results. This was done by different items to establish if they measured the same general construct. A correlation coefficient using the Pearson product moment correlation coefficient was then calculated to show the relationship between the sets of scores.

3.7.1.1 Piloting of Research Instruments

The study checked for quality control to ensure that errors were eliminated in the tool during the development, analysis and presentation of this study. Quality control measures included; Piloting to test for reliability and validity, standard referencing, data screening and cleaning. Arain et al., (2010) define a pilot study as a small study to test research protocols, data collection instruments, sample recruitment strategies, and other research techniques in preparation for a larger study. It assists in eliminating ambiguous questions as well as in generating useful feedback on the structure and flow of the intended interview and prevents the occurrence of a fatal flaw in a study that is costly (Polit & Beck, 2017).

A pilot study was conducted at Sang'alo Institute of Science and Technology- now Bungoma National Polytechnic. The pilot involved administering questionnaires to 20 respondents, aimed at ensuring quality control by minimizing errors in the study's development, analysis, and presentation stages (Arain et al., 2010; Baker, 2016). This preliminary step tested research protocols, data collection instruments, and recruitment strategies, providing critical feedback on question clarity and interview flow (Thabane et al., 2010)

Reliability and validity were the pilot's primary focuses. Reliability, defined as the consistency of results across multiple measurements (Fallon, 2016; Babbie, 2014; 2008) was assessed using an average inter-item correlation. This method tested internal consistency by determining if individual questions consistently measured the same construct (Tavakol & Dennick, 2011).

Pearson product moment correlation coefficient was used to determine the correlation coefficient ($\Gamma^1{}_x$). The reliability of the entire instrument was obtained through $\Gamma^1{}_{xx} = 2\Gamma_{xx} / (1 + \Gamma_{xx})$, where Γ_{xx} is the correlation between the two tests. Below is the result for the reliability of the questionnaires.

$$\frac{2 \times 0.7581}{1.7581} = 0.8624$$

Since the questionnaires had a reliability of 0.8624 which is greater than 0.8, the questionnaires were established to be reliable and indicating strong internal consistency and ensuring that the questions provided dependable results (Nunnally & Bernstein, 1994).

However, the pilot study's outcomes highlighted several areas for improvement in the questionnaire. Feedback indicated that some questions were ambiguous, leading to varied interpretations among respondents, consistent with Polit and Beck's (2017) assertion that pilot studies help eliminate ambiguities. Specifically, questions regarding income were reframes to separate wage earnings from business earnings. Questions on Institutional teaching resources on likert scale were rephrased for clarity, ensuring that all respondents understood them uniformly (DeVellis, 2017). Moreover, the flow of the questionnaire was adjusted to enhance logical progression and respondent engagement based on feedback received (Brace, 2018).

Additionally, the pilot study revealed some gaps in the questionnaire regarding the measurement of employment outcomes. To address this, new questions were added to capture a broader range of employment metrics, such as such as migration and number of job applications. (Holtom et al., 2008). These adjustments were informed by recent literature emphasizing the multifaceted nature of employment outcomes (Kalleberg, 2011). (Fowler, 2014). Furthermore, the pilot study resolved issues related to data collection methods. For instance, telephone interviews faced challenges such as reaching non-existent phone lines, respondents perceiving calls as potential scams, and low response rates from female respondents (Groves et al., 2009; de Leeuw, 2004). De Leeuw, 2005). Solutions to these challenges included employing female research assistants to increase response rates from women (Holt & Walker, 2019), asking registrars to inform alumni to expect a call, shortening the length of the questionnaire, and omitting obvious demographic questions like gender to save time (Dillman et al., 2014). These adjustments were aimed at improving response rates and the overall quality of the data collected.

In conclusion, the pilot study at Bungoma National Polytechnic was instrumental in refining the research instruments, enhancing question clarity, ensuring logical flow, and expanding the scope of employment outcome metrics (Bryman, 2016). These adjustments, grounded in both feedback from the pilot and recent academic insights, improved the validity and reliability of the main study's data collection process. (Creswell J. , 2014; Maxwell, 2012)

3.7.2 Validity

The face and content validity of the questionnaire was established through consultation with experts from the department of educational management and planning at Masinde Muliro University of Science and Technology. This phase was aimed at exploring the theoretical constructs and how these constructs were represented in an operational measure in the questionnaires (Bhattacherjee, 2012).

On Content validity, literature reviews was done followed by an evaluation of the research instruments by the researcher's academic advisors and other experts from the department. Their suggestions and clarifications were used to improve representation of the content that was investigated. A content validity survey was generated where each item was assessed using a three-point scale (not necessary, useful but not essential and essential).

The content validity evaluation using Lawshe's (1975) method, with a a panel of 6 experts was done. Of these, 4 experts rated the item as "essential." The Content Validity Ratio (CVR) was calculated using the formula CVR= $\frac{n_e - \frac{N}{2}}{\frac{N}{2}}$ where n_e is the number of experts rating the item as essential, and N is the total number of experts. Substituting the values, the CVR was computed as; CVR= $\frac{4-3}{3}$ = 0.333. This value represents the minimum threshold required for the item to be considered valid according to Lawshe's criteria (Lawshe, 1975).

3.8 Methods of Data Analysis and Presentation

3.8.1 Data Screening and Cleaning

Data was screened and cleansed to ensure completeness. It involved identifying and correcting errors, inconsistencies, or missing data in employment, wages, and demographic variables (Tabachnick and Fidel, 2013). This process ensured that the data used for analysis accurately represented the population and avoided biases or misinterpretations that could affect conclusions about labour market outcomes.

3.8.2 Data Coding

Data coding involved transforming raw data into a structured format that were easily analysed, processed, or understood by STATA software. It involved assigning meaningful labels, numbers, or codes to information for easier handling and interpretation, such as converting categorical responses into numerical values or encoding non-numeric data into a numerical format.

3.8.3 Quantitative and Qualitative Data Analysis

Qualitative data was analysed through theme identification that explained or added context to the quantitative results. The quantitative aspect utilized univariate, bivariate and multivariate analysis.

3.8.4 Univariate, Bivariate and Multivariate Analysis

The univariate analysis examined the distribution of single-variable values using means, standard deviation, standard errors, percentages, and frequencies for employment status, earnings, job search duration, and sector employment. Bivariate analysis included correlation computation, chi-square, and t-tests to explore relationships between explanatory and outcome variables. Multivariate analysis involved multiple regression, multinomial logistic regression, binary logistic regression, and survival analysis to examine connections among more than two variables.

3.8.5. Analysis Plan of Objectives.

The outcome variable for objectives 1-3 were; employment status measured on a nominal scale, earnings measured on a ratio scale, unemployment duration measured on a ratio scale, and sector of employment measured on a nominal scale. Data of respondents on employment statuses included; employed in the area of study, employed in field of study, employed in different field of study, self-employed the field of study, self-employed in a different field of study, unemployed. The univariate analysis comprised of computing frequencies, percentages, means, and standard deviations. For example, the mean earnings by nature of STEM academic programs computation are shown in table 4.11. Similarly, the mean earnings by the level of STEM academic certificate is shown in table 4.20. The bivariate analysis for example computed a t-test to compare the means of earnings for modular and non- modular programs to determine if there was a significant difference between them. Multivariate analysis utilized a multinomial logit model to predict employment statuses and survival analysis using the parametric method to analyse time to employment. The results of the univariate, bivariate and multivariate analysis are presented in sections 4.4, 4.5 and 4.5 of the thesis.

The outcome variable for the fourth objective was Employment status measured as a ratio scale variable. The Structural Equation Model results sought to establish the link between employment status and predictor variables such as curriculum resources, training resources, career services resources, and teaching resources. The results of the univariate, bivariate and multivariate analysis are presented in section 4.7 of the thesis. The table 3.5 gives a summary of analysis as per the research objectives.

Table 3.5: Summary of Method Analysis as Per Research Objectives

Objective	Variables	Variable Label	Outcome Variable	Measurement Scale	Analysis Type
1	E.V	Nature of Course	Employment Statuses	Nominal	Univariate statistics, t-test Multinomial Logit
			Earnings	Ratio	Regression Analysis
			Job search duration	Ratio	Survival Analysis
			Sector Employed	Nominal	Binary Logit Model
2	E.V	Level of Certificate	Employment Status	Ordinal	Descriptive statistics, Multinomial Logit
			Earnings	Ratio	Regression Analysis
			Job search duration	Ratio	Survival Analysis
			Sector Employed	Nominal	Binary Logit Model
			Employment Status	Nominal	Descriptive statistics, Multinomial Logit
3	E.V	Field of Study	Earnings	Ratio	Regression Analysis
			job search duration	Ratio	Survival Analysis
			Sector Employed	Nominal	Logit Model
4	E.V	Training Resources	Employment Category	Nominal	Structural Equation Model

3.9.2.4 Survival Analysis

The event of exiting from unemployment to employment of graduates of STEM programs within the NPs in Kenya was examined using survival analysis. Survival meant a graduate who retained the status of unemployment at the end of the study period. A graduate who exited from the unemployment status to employment status is said to have experienced a failure event.

Parametric analysis was utilized to compare the probability of exit (from unemployment to employment status) between subgroups where the expected probability of exit was calculated under the null hypothesis that the survival curves were equal in both groups. The event of occurrence for employment (yes/no) was selected as the dependent variable. Each individual was considered to have survived for each of the time periods analysed, if they had not exited the unemployment status at some previous time; If a graduate exited from unemployment status to employment, then survival would not have occurred.

Control variables included; gender, level of course, type of course, course duration, and course advancement. The maximum survival time (T) between those in employment and those in unemployment were measured in months (65months). The study assumes that the first cohort to enter the job market was 2017 for the artisan graduates, 2018 for the craft and higher diploma graduates and 2019 for the diploma graduates. To ensure reliable estimates, the study controlled for the year of graduation.

The cumulative distribution function F of the duration of time T was formulated as follows:

$$F(t) = P\ (T \leq t)\ , 0 \leq t \leq 65 \quad \ldots\ldots (1)$$

The probability function denotes that the duration of time T is less than or equal to t.

The probability of survival was analysed for the different time periods in months with effect from the time of completion of studies. The study used parametric methods to estimate survival curves with 95% confidence intervals.

The survival function is defined as follows:

$$S(t) = 1\text{-}F(t) = P\ (T > t) \quad \ldots\ldots (2)$$

This function represents the probability of survival at a past time t and is calculated using the estimating the function;

$$\hat{S}(t) = \prod t_1 \leq t(1 - \frac{d_i}{n_i}) \quad \ldots\ldots (3)$$

Where $\hat{S}(t)$ calculates the probability of the survival of graduates after a time t, and t being the duration of the study at a point i; d_i is the number of exits from unemployment up to point i. This represent the number of graduates who successfully get employment opportunities in the study period and therefore would not have survived); and n_i is the number of respondents at risk before t_i.

3.9.2.5 Diagnostic Test for Survival Analysis

In this model, graduates exit either by getting employment or through right censoring events. The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were used to assess model fit while penalizing for complexity. Lower AIC/BIC values indicate a better balance of fit and simplicity

3.9.2.6 Multinomial Logit Model

A multinomial logit model was designed to handle J + 1 responses, for $J \geq 1$

Assume a response of the form

$$\Pr(yt = l) = \frac{exp(Wtl\beta^{l})}{exp(Wtj\beta^{j})} \quad \text{for } l = 0, 1, 2 \ldots\ldots\ldots j. \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(4)$$

A multinomial logit model was estimated in which labour market outcomes were modelled as a function of the nature of academic programs, level of academic programs, and type of academic programs, plus a range of control variables such as age, gender, migration, and reservation wage. The outcome variables in the multinomial logit model were employment status (employed in the field of study, employed in a different field of study, self-employed in the field of study, self-employed in a different field of study, and unemployed). The explanatory variables in this model included; the nature of the academic program (modular or non-modular), the level of the academic program (artisan, craft, diploma, higher diploma), and the field of study.

3.9.2.7 Diagnostic Test Multinomial Logit Model

The study tested various assumptions of the multinomial logit model. These included; linearity, outliers' independence, independence of Irrelevant Alternative (IIA), and the cooks Distance measure.

3.9.2.8 Likelihood Ratio Test

The test is based on the -2 Log Likelihood (LL). The Likelihood ratio test gives a chi-square statistic that tests the null hypothesis that there is no significant difference between the models without explanatory variables and the model with explanatory variables.

3.10 Ethical Consideration

This study was approved by Masinde Muliro University Review Board before proceeding to the field for data collection. Consent was sought from all the research participants before they responded to the interview. A letter was written to registrars and office of career officers requesting them to participate in the interviews and Focus Group Discussion. A research permit from the National Council of Science, Technology, and Innovation (NACOSTI) upon successful defence of the proposal and approval from the University was issued.

CHAPTER FOUR

PRESENTATION, INTERPRETATION AND & DISCUSSION OF FINDINGS

4.0 Overview

This chapter entails data presentation, interpretation and discussion on the effect of STEM program characteristics on labour market outcomes of graduates of NPs in Kenya. The results of this study are presented in form of tables and figures and discussed in the context of objectives, in section 4.4, 4.5, 4.6 and 4.7 after the response rate, preliminary analysis tests and summary of descriptive statistics presented in 4.1, 4.2 and 4.3 respectively.

4.1 The Response Rate

A total number of 1834 telephone interviews were made. Out of these, 1473 gave complete responses. This accounted for 80.31.3% of the valid response rate. A response rate of at least 30% is acceptable for surveys (Hair et al., 2019). In addition, interview schedule and focus group discussion gave a 100% response rate.

4.3.1 Distribution of Respondents

Table 4.1 shows the distribution of respondents in different institutions.

Table 4.1 Sample Size Per Institution

Institution	Freq.	Percent	Cum.
Eldoret National Polytechnic	267	18.29	18.29
Kabete National Polytechnic	119	8.15	26.44
Kenya School of TVET	154	10.55	36.99
Kenya Coast National Polytechnic	91	6.23	43.22
Kisii National Polytechnic	133	9.11	52.33
Kisumu National Polytechnic	186	12.74	65.07
Kitale National Polytechnic	98	6.71	71.78
Meru National Polytechnic	125	8.56	80.34
North Eastern National Polytechnic	92	6.30	86.64
Nyeri National Polytechnic	118	8.08	94.73
Sigalagala National Polytechnic	90	5.27	100.00
Total	1473	100.00	

Eldoret National Polytechnic had the highest number of sample size with 267, making up 18.29% of the total represented. The data further revealed significant variations in the number of respondents across institutions. For example, Kenya Coast National Polytechnic had 91(6.23%) of the total sample represented. Overall, table 4.1 provides a clear visual representation of the distribution of graduates in different NPs.

From this enrolment distribution, it can be argued that higher number of graduates from a polytechnic might suggest a more extensive alumni network and potentially better job placement opportunities, whereas institutions with fewer graduates might reflect different employment challenges or opportunities. Thus, enrolment distribution data is essential for understanding and interpreting the broader implications of educational backgrounds on labour market outcomes.

4.2.1. Data Coding and Screening

The survey data was screened for several potential problems concerning missing data according to guidelines provided by Tabachnick and Fidell, (2013). The significance of data screening in any process of data analysis particularly quantitative surveys cannot be over-emphasized because it provides an excellent groundwork for the achievement of a significant result. The output and analysis quality are dependent upon the quality of preliminary data screening (Hair et al., 2019). The survey data, collected through telephone interviews and managed using KoBoToolbox software, underwent a rigorous process of data coding and screening to ensure quality and accuracy.

Responses were systematically coded, with open-ended answers categorized into thematic codes and quantitative responses converted into numerical formats, while a coding dictionary was maintained for consistency. During data screening, the dataset was thoroughly examined for inconsistencies, missing values, and outliers. Required fields were checked for completeness, and any anomalies were addressed according to predefined protocols, such as imputation or exclusion of missing data. Outliers were investigated to determine their validity, ensuring that the final dataset was accurate, reliable, and ready for statistical analysis.

4.2.1.1 Coding of Variables

The study had several variables which were coded as shown in table 4.2

Table 4.2 Coding of Variables

Variable Description	Variable Code	Codes/Values
Nature of Course	A14_NatureofCourse	Modular =1 Non-Modular =0
Level of Certificate	A15_LevelofCert	Artisan=1, Craft =2, Degree=3, Diploma =4, Higher Diploma=5
Field of Study	Field_of_Study	Information & communication Technology=1, Agriculture & Environmental Studies=2, Applied Sciences=3, Building & Civil Engineering=4, Electrical & Electronics engineering=5, Health Sciences=6, Hospitality & Institutional Management=7, Mechanical Engineering=8
Gender	Gender	Male = 0 Female = 1
Migration Dummy	A6_MigratDummy	Migrated=1 Did Not Migrate=0
Marital Status	A9_MaritalStatus	Married =1 Not Married= 0
Employment Category	EmployCat	Employed in different field=1, Employed in own field of study= 2, In Training = 3, Self-employed in different field= 4, Self-employed in same field=5, unemployed =6
Sector Employed	Sector	Public =1, Private = 0
Migration	Migration_Dummy	Migrated =1, Did not migrate =0
Marital Status	Marital_Status	Married =1, Not Married =0
Education Sponsor	Educsponsor	County Government/CDF=1, NYS=2, Religious organization/NGO= 3, Self-Sponsored /Parents/Guardian=4, Government capitation/HELB=5
Exam Grade	Examgrade	Distinction=5, Credit =4, Pass= 3, Refer= 2, Fail= 1
Job Search Intensity	JSI	Low JSI= 1, Medium JSI =2, High JSI =3
Social Capital	Scapital	Low SCapital= 1, High SCapital =0
Course Advancement	CourseAdvance	Advance one grade=1, Advance 2 Grades= 2
Migration TO	migration_TO	Did not move- in Urban =1 Did not move-in Rural=2, From Rural to Rural=3, From Rural to Urban =4, From Urban to Rural=5, Urban to another Urban=6
Academic Qualification	AcadQual	Artisan=1, Craft =2, Degree=3, Diploma =4, Higher Diploma=5

4.2.1.2: Computation of Job Search Intensity

To analyse the job-search intensity among respondents, Principal Component Analysis (PCA) was performed using various job search methods, including "Friends and Relatives," "Newspaper Advertisement," "Social Media Platforms," "Direct

Applications," "Voluntary Service as Internship," "Employment Agencies," "Dial Platforms," "Personal Contacts," and "Spontaneous Applications." This method helped identify the key components that capture the underlying patterns in how respondents used these methods. The PCA results were further analysed using factor analysis to determine the relationships among these variables.

The Kaiser-Meyer-Olkin (KMO) measure was calculated to assess the sampling adequacy, ensuring that the data was suitable for this type of analysis. The factors were then rotated and normalized to simplify the interpretation. Following the PCA and factor analysis, the first principal component (Comp1) was predicted and renamed "jsi" to reflect its role as a comprehensive measure of job search efforts. The scores were then categorized into three quantiles labelled as "Low," "Medium," and "High" job search intensity. This categorization helped in understanding the varying levels of job search activity across respondents, facilitating a more nuanced analysis of how different job search strategies contribute to overall efforts.

4.2.2 Assessment of Outliers

This study assessed both univariate and multivariate outliers. Univariate outliers were detected using standardized variable values (z-scores) or frequency distribution tables such as histograms, box plots, and normal probability plots. Following the threshold suggested by Tabachnick and Fidell, (2013), z-scores exceeding 3.0 or less than -3.0 were considered outliers. Consequently, three cases were identified as potential univariate outliers using standardized values. These univariate outliers were deleted from the dataset to ensure the accuracy of the data analysis.

4.3. Summary of Descriptive Statistics

The outcome variables for the study were: - Employment status, Earnings/Wages, unemployment spell, and sector employed. The frequencies, percentages, means, standard deviation, and standard errors were performed for the following variables; Nature of Course-Modular and non-modular; level of academic certificate- artisan, craft, diploma, higher diploma; Field of study- variables from 8 fields of study. Univariate analysis was performed on the control variables. This included; age, gender, marital status, migration, reservation wage, and job search intensity among others. Results were presented in the form of tables, figures, and charts.

Descriptive Statistics of variables used in the Analysis of Data

Table 4.3 shows the descriptives statistics of variables used in the study.

Table 4.3

Variable	Obs	Mean	Std. dev.	Min	Max
Nature of Course	1,473	1.40	0.49	1	2
Field of Study	1,473	5.73	2.31	1	9
Level of Certificate	1,473	2.63	0.67	1	4
Gender	1,473	1.64	0.48	0	1
Marital Status	1,473	1.41	0.49	0	1
Age	1,473	29.82	3.03	23	41
Unemployment Spell	1,473	23.22	17.80	0	65
Examgrade	1,473	2.85	1.35	1	5
CourseAdvance	1,473	1.22	0.45	1	3
AcadQual	1,473	3.60	0.89	1	5
jsi	1,473	1.84	0.85	1	3
migration_1	1,473	1.67	0.47	1	2
migration_TO	1,473	3.82	0.72	1	6
SocialCapital	1,437	0.00	0.62	1.72	0.41
Educsponsor	1,473	6.17	0.85	1	7
Migrationdummy	1,473	1.67	0.47	1	2
JobApplications	1,473	2.64	2.61	0	16

Note. Min=Minimum; Max=Maximum; Std.Dev.=Standard Deviation; Obs=Observation

Summary statistics for various variables, each measured across 1,473 observations have been shown. The mean values for the variables range from 1.22 (CourseAdvance) to 6.17 (Educsponsor), with standard deviations varying between 0.45 (CourseAdvance) and 2.61 (JobApplications). The minimum and maximum values show the range of responses for each variable, such as ages between 23 and 41, or job applications ranging from 0 to 16. The data includes both categorical variables (e.g., Gender and Marital Status) and continuous variables (e.g., Age and Unemployment Spell).

4.4 The Nature of STEM Academic Programs on Labour Market Outcomes

The first objective was to establish the effect of the nature of STEM academic programs on the labour market outcomes of graduates of national polytechnics in Kenya. The data was analysed and presented in the following sequence: First, the distribution of the nature of the course as modular versus non-modular has been outlined; second, regression analysis has been conducted to examine the impact of the nature of the course on earnings; third, multinomial regression analysis has been employed to a assess the relationship between the nature of the course and employment status; forth, a survival analysis has been performed using the semi paramedic Cox proportional hazards and the Weibull parametric method to analyse the time-to-event(Unemployment to employment) data of respondents.

4.4.1 Distribution of the Nature of Course

This objective categorized the respondents based on the nature of their courses, shedding light on the distribution between modular and non-modular programs. The results are presented in figure 4.1

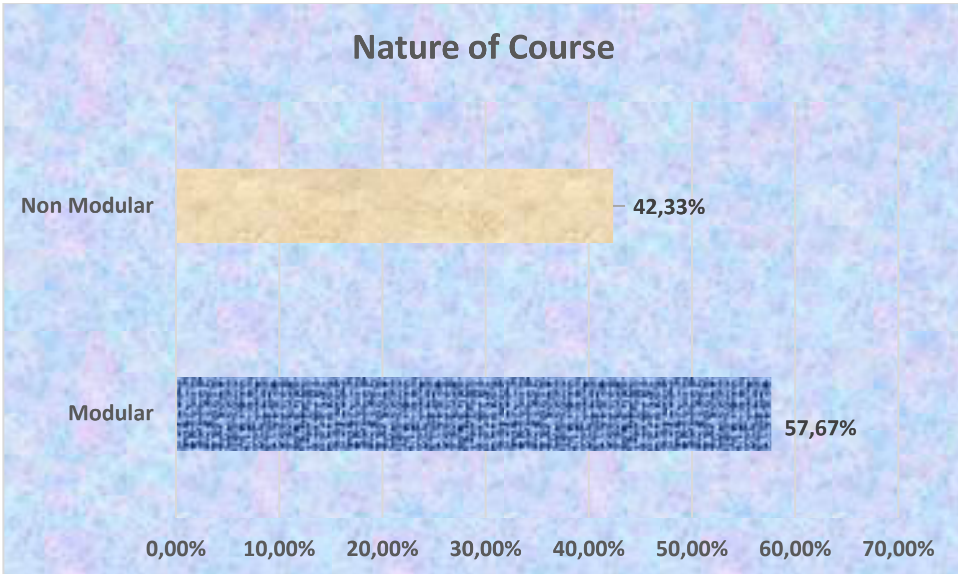

Figure 4.1: Nature of Course

Majority of respondents, 57.67%, enrolled in "Modular" courses while 42.33%, were enrolled in "non-Modular" courses. Previous findings on the nature of the course and labour market outcomes have shown varying trends in enrolment patterns and their implications for employment outcomes among Technical and Vocational Education and Training (TVET) students. Studies by Smith et al. (2018) indicated a growing preference for modular courses among TVET students due to their flexibility and adaptability to changing labour market demands. The findings concur with those of Weise & Christensen (2014), who posit that modularization enables training institutions to easily arrange modules of learning and package them into different, scalable programs for different industries and thereby provide a wide range of employment opportunities for the TVET graduates. Conversely, Johnson & Lee (2020) and Jones & Brown (2020) highlighted the continued popularity of non-modular courses, particularly in traditional vocational fields.

Interview results with the registrar revealed that the "*shift towards modular courses is driven by the need to align training with industry demands and the evolving workforce. Modular curricula courses include emerging skills, contributing to their popularity because of their flexibility.*" The Focus Group Discussions (FGDs) with career officers further indicated that students in modular programs tend to have more employment opportunities, as these courses equip them with practical, industry-relevant skills. However, non-modular courses remain attractive in traditional vocational fields where specialized training is crucial. The ongoing TVET reforms reflect this shift towards modular programs to address industry skill gaps.

4.4.2 Nature of Course and Earnings

This section explored the relationship between the nature of course-modular or non-modular—and the subsequent earnings of graduates. Table 4.4 shows the t-test results of earnings between modular and non-modular programs.

Table 4.4: T-Test for Nature of Course and Earnings

Nature of Course	**Mean**	**Std. err.**	**[95% conf.**	**interval]**
Modular	13280.98	862.96	11588.22	14973.74
Non-Modular	11010.96	1007.09	9035.472	12986.44
Diff(mean)	2270.03	1336.94	-352	4892
	t = 1.6979,	D.F = 1471		P= 0. 0449

A two-sample t- test with equal variances was performed. The results showed that the mean earnings for the different nature of academic programs were statistically significantly different from zero t (1471) = 1.69, p = 0.0449). The nature of the academic programs had a meaningful impact on earnings. Following the observation of the statistical significance in the t-test, the subsequent step involved conducting a multivariate analysis- regression analysis to identify which predictors significantly influenced earnings.

4.4.3 Regression Analysis of Nature of Course on Earnings

Regression analysis of the nature of course structure- modular or non-modular, on earnings was performed to assess the impact of course format on graduate income. This analysis aimed to determine whether the nature of academic programs significantly influenced earnings, to understand how different types of educational programs affected students' future income.

This was preceded by regression diagnostic tests.

The general regression was given by;

$$Y=\beta 0+\beta_1X_1+\beta_2X_2+\cdots+\beta_kX_k+\epsilon$$

Where Y = Earnings, β_0 = Intercept/constants, β_1,$\beta_{2,,}$ $\beta_,$ β_k are regression coefficients of respective predictors, and X_1, $X_{2...}$,X_k are independent variables, ϵ = Error term. The

Predictor was the Nature_of_Course. The study included several control variables to account for factors that could potentially influence total earnings. These control variables were **Gender**, **Gender#c.Nature_of_Course** (the interaction between gender and nature of course), **Employment Category (EmployCat)**, **Migration Status (migration_TO)**, **Reservation Wage (ReservationWage)**, **Exam Grade (Examgrade)**, and **Marital Status (Marital_Status)**. By including these variables, the analysis controlled for the effects of gender, employment status, migration patterns, academic performance, expected wages, and marital status, allowing for a more accurate assessment of the relationship between nature of the course and total earnings.

4.4.3.1 Assumptions of the Multiple Linear Regression

The study made several key assumptions for the linear regression analysis. These assumptions included (1) linearity, meaning that a linear relationship existed between the independent and dependent variables; (2) independence, ensuring that the observations were independent of one another with no autocorrelation in the residuals; (3) homoscedasticity, indicating that the variance of the residuals was constant across all levels of the independent variables; (4) normality, where the residuals were approximately normally distributed, particularly for significance testing; and (5) no multicollinearity, meaning the independent variables were not highly correlated with one another. Violations of these assumptions could have led to biased or inefficient estimates, thus affecting the validity of the regression results.

The regression analysis assumptions were examined using the Stata regcheck function as proposed by Mehmetoglu (2014). It invoked the Breusch-Pagan test, computed Variance

Inflation Factors, the Shapiro-Wilk test, the link test, the Ramsey Specification Error Test (RESET) test, and Cook's distance test. Table 4.5 gives a summary of the diagnostic tests.

Table 4.5 Regression Diagnostics Tests

Regression assumptions	**Test**	**We seek values**	**Decision**
1) Heteroskedasticity	Breusch-Pagan Chi2(1): 1178.575 p-value: 0.000	**> 0.05**	Perform robust
2) Multicollinearity problem	Variance inflation	**< 5.00**	
	Nature_of_Course	1.05	
	EmployCat	4.57	
	Examgrade	3.04	
	jsi	2.9	
	Educsponsor	2.29	
	Marital_Status	1.43	
	Scapital	1.3	
	Gender	1.21	
	AcadQual	1.16	
	ReservationWage2	1.09	
	Applications8wks	1.08	
	CourseAdvance	1.06	
	migration_TO	1.04	
	Migration_Dummy	1.02	
3) Residuals are not	Shapiro-Wilk W t: 11.216 p-value: 0.000	**> 0.01**	
4) Specification problem	Linktest t: 11.216 p-value: 0.000	**> 0.05**	
5) Functional form problem	Test for appropriate F(3,1417):62.771 p-value: 0.000	**> 0.05**	
6) No influential	Cook's distance no distance is above	**< 1.00**	

Source Researcher, 2024

As shown in table 4.12, several underlying assumptions of the regression were diagnosed. Results showed that the normal OLS did not meet the normal regression equation assumptions for heteroskedasticity, multicollinearity, and normality including functional form problems. Consequently, this led to the use of robust multiple linear regression that ensured the standard errors obtained using the Huber-White sandwich estimator were robust to heteroscedasticity and other forms of misspecification (King & Roberts, 2015; Mansournia, 2021).

Table 4.6 Multiple Linear Regression of Earnings on Nature of Course

Total_Earnings	Coefficient	Robust std. err.	t	P>t
Nature_of_Course				
Modular	4757.17	1945.24	2.45	0.015
Gender				
Female	-3001.8	1383.31	-2.17	0.030
Gender#c.Nature_of_Course				
Male	-6323.97	2260.09	-2.80	0.005
EmployCat: base Employed in different field of study				
Employed in my field of study	15696.3	6065.83	2.59	0.010
In Training	-23022	5953.69	-3.87	0.000
employed in different field of specialization	-23834.8	5872.96	-4.06	0.000
Self employed in field of specialization	-24150.8	5858.76	-4.12	0.000
Unemployed	-23594.3	5875.54	-4.02	0.000
migration_TO				
From Rural to Urban	1259.22	628.12	2.00	0.045
From Urban to another Urban	6275.36	2721.13	2.31	0.021
EmployCat#c.Field_of_Study				
Employed in a different field of study	2090.40	1226.98	1.70	0.089
ReservationWage2	-0.05	0.04	-1.49	0.138
Examgrade				
Fail	-3269.04	1361.49	-2.40	0.016
Pass	-1079.63	1112.20	-2.05	0.041
Refer	-2262.86	1614.65	-2.52	0.012
Marital_Status				
Married	1668.08	759.33	2.20	0.028
_cons	26602.04	6195.50	4.29	0.000

Note: Number of obs= 1473, F(16,1456)= 76.81, Prob > F= 0.000, R-squared= 0.5345, Root MSE= 17278

The regression analysis in table 4:6 shows findings regarding the nature of course and other control variables on total earnings. The model was statistically significant F(16, 1456) = 76.81), p <0.001) with a high predictive power (R^2= 0.5345) and an adjusted R-squared of 0.5283 demonstrating that approximately 53.79% of the variability in total earnings was accounted for by the predictor variables.

Graduates who pursued modular programs were associated with statistically significant increase in total earnings by approximately Ksh. 4757.17($p = 0.015 < 0.05$) compared to non-modular programs. Additionally, females graduates earned Ksh. 3001.8 less compared to male graduates ($p< 0.05$). Controlling for exam grades, failing an exam was associated with a significant decrease in total earnings by Ksh. 3269.04($p= 0.016< 0.05$) compared to a "Credit" pass. Similarly, graduates who scored a "Refer" earned Ksh. 2262.86 less compared to those who scored a "Credit" pass. ($p= 0.041$).

Employment categories showed varied effects on earnings. Being employed in one's field of study significantly increased total earnings by Ksh. 15696.3($p = 0.010 < 0.05$) compared to being employed in a different field of study. In contrast, being in training was associated with a statistically significant decrease in earnings by Ksh. 23022($p = 0.004< 0.05$) compared to being employed in a different field of study. Being self-employed in a different field of study resulted in a decrease in earnings of Ksh. 23834.8 ($p =0.000< 0.05$) compared to being employed in a different field of study. Similarly, being self-employed in the field of study decreased earnings by Ksh. 24150.8 ($p= 0.000 < 0.05$) compared to being employed in a different field of study. Alina (2012), showed that education may influence several labour market outcomes, such as wages and earnings. When controlling for the year of graduation, there was no statistically significant effect of nature of course on earnings.

In addition, those who migrated from rural to urban areas earned an additional Ksh 1259.22, ($B = 1259.22$, $SE = 628.12$, $t = 2.00$, $p = 0.045$) compared to those who lived in urban area. Those who migrated from urban to another urban area earned an additional

Ksh 6275.37, (B = 6275.37, SE = 2721.13, t = 2.31, p = 0.021) compared to those who lived in urban area but had never moved. Further, marital status was also significant, with married respondents earning, on average, Ksh 1668.08 more than their unmarried counterparts, (B = 1668.08, SE = 759.33, t = 2.20, p = 0.028).

These results seem to suggest that graduates who pursued modular programs have higher earnings compared to those who pursued non-modular programs.

The null hypothesis for this sub hypothesis was;

$H_0 1(a)$: The nature of STEM academic programs has no statistically significant effect on earnings of graduates of national polytechnics in Kenya. From the results discussed in section 4.4.2, the study rejected the null hypothesis at $\propto = 0.05$ and concluded that the nature of STEM academic program has a statistically significant effect on earnings of graduates of national polytechnics in Kenya.

The findings of the study, indicating that graduates who pursued modular programs earned significantly more than those in non-modular programs (Ksh 4757.17), align with literature suggesting that specialized and flexible learning pathways can enhance employability and earnings. Modular programs are often designed to be more responsive to labor market needs, offering practical and relevant skills (Klein & Tuma, 2019). Such programs allow students to tailor their education to specific industries or career goals, which may improve their job prospects and earning potential (Harris & Smith, 2016). However, some scholars argue that the long-term benefits of modular programs depend on industry-specific demand and the availability of relevant job opportunities (Collins et al., 2020). In contrast, other studies highlight that the prestige of the institution or the professional network it provides may have a greater influence on earnings than the format of the program (Hoxby, 2017).

The significant gender disparity in earnings, with female graduates earning Ksh 3001.8 less than their male counterparts, is consistent with the well-documented gender wage gap. Research by Blau and Kahn (2017) and Goldin (2014) emphasizes that even in similar educational contexts, women continue to face lower wages due to a combination of factors including discrimination, occupational segregation, and differences in career progression opportunities. Some scholars argue that gender differences in negotiating salaries or choices of lower-paying industries might explain part of the wage gap (McKinsey & Company, 2020). However, others suggest that the gender wage gap is largely driven by structural inequalities in the workplace, including unconscious biases and disparities in promotions (Booth et al., 2019). The findings of this study further support these broader trends, highlighting the persistent challenge of achieving gender pay equity.

The negative impact of failing an exam or receiving a "Refer" grade on total earnings (Ksh 3269.04 and Ksh 2262.86, respectively) is in line with research showing that academic performance is a strong predictor of future earnings. Academic achievement often signals higher cognitive ability, work ethic, and persistence, qualities that employers value highly (Oreopoulos & Salvanes, 2011). Furthermore, strong academic performance is associated with better job opportunities and higher salaries (Carnevale et al., 2018). However, some critics argue that focusing on academic performance alone may overlook other factors that influence earnings, such as internships, work experience, and personal networks (Becker, 2020). Moreover, while academic performance correlates with earnings, it does not necessarily account for the disparities in earnings observed across different fields of study or industries (Lemieux, 2018). Thus, while exam grades remain an important determinant of earnings, they do not provide a complete picture of the factors influencing graduates' financial outcomes.

The findings from this study align with previous research indicating that migration status significantly influences earnings. Specifically, respondents who migrated from rural to urban areas experienced higher earnings compared to those who remained in urban areas. This supports existing literature suggesting that migration can provide access to better job opportunities and resources, thereby increasing income potential (Mincer, 2018; Clark & Drinkwater, 2019). Urban areas are generally more economically diverse, offering a wider range of employment opportunities and higher wages (Glaeser & Maré, 2018). Additionally, those who migrated from one urban area to another also saw significant income increases, suggesting that even within urban settings, geographical mobility can open up better job prospects. This is consistent with Borjas (2017), who argues that moving within urban environments can enable workers to access specialized labor markets that offer better-paying roles.

Marital status was another significant factor affecting earnings in this study. Married respondents earned more than their unmarried counterparts, a result that mirrors findings in the broader literature on the economic benefits of marriage. Research suggests that married respondents often experience greater financial stability and increased earnings potential due to shared resources and dual-income households (Korenman & Neumark, 2019). Marriage may also provide respondents with access to more stable job opportunities and career advancements, contributing to higher earnings (Schultz, 2017). However, some studies caution that the marriage premium on earnings can vary depending on factors such as education, occupation, and age (Smock et al., 2019). While the positive relationship between marriage and earnings is widely supported, these variations indicate that marriage alone does not guarantee higher earnings without considering other socio-economic factors.

4.4.4 Nature of Course and Employment Status

The second sub-hypothesis study sought to establish the effect of the nature of course programs on employment status. Employment statuses include; Employed in a different field of study, Employed in field of study, in Training, Self-employed in different fields of study, Self-employed in field of study, and Unemployed. The explanatory variable was nature of course- Modular and non-modular. Control variables were; Gender, A10_Age, SpellDuration, migration_TO, AcadQual, Scapital, CourseAdvance, jsi, Examgrade, Marital_Status, Migration_Dummy, ReservationWage,2 Applications8wks, and course duration year of graduation. The results of descriptive statistics are outlined in table 4: 14.

Table 4:7 Descriptive Statistics

Employment Status	% Modular	% Non-Modular	% Total
Employed in a different field of study	5.77	3.39	9.16
Employed in my field of study	14.46	8.08	22.54
In Training	1.22	0.95	2.17
Self-employed in different fields of study	8.83	4.75	13.58
Self-employed in field of study	5.97	3.6	9.57
Unemployed	23.42	19.55	42.97
Total	59.67	40.33	100

The table 4.7 provides information about the employment status of respondents, categorized by whether they were in modular or non-modular programs of study. Of the total respondents, 59.67% were from modular programs, and 40.33% from non-modular programs. A higher percentage of modular program graduates were employed in their field of study (14.46%) compared to non-modular graduates (8.08%). Further, non-modular graduates showed a slightly lower percentage of being employed in a different field of study (3.39%) than modular (5.77%). Self-employment in the field of study was also common among modular programs (5.97%) compared to non-modular ones (3.6%). Unemployment was notably high overall at 42.97% with high rate among modular graduates (23.42%) than non-modular graduates (19.55%). The results revealed that while modular programs offered better alignment with field-specific employment, they also showed a slightly higher rate of unemployment compared to non-modular programs.

A chi square test was performed to establish if there was any association between employment status and nature of the course.

Table 4.8 Chi square test for Nature of Course and Employment Status

	Employed in a different field of study	Employed in my field of study	In Training	Self employed in different field of study	Self employed in field of study	Unemployed	Total
Non-Modular	50.00	119.00	14.000	70	53	288	594
	37.04	35.84	43.750	35	37.59	45.5	40.33
Modular	85.00	213.00	18.000	130	88	345	879
	62.96	64.16	56.250	65	62.41	54.5	59.67
Total	135.00	332.00	32.000	200	141	633	1,473
	100.00	100.00	100.000	100	100	100	100

Pearson chi2(5) = 13.3670 Pr = 0.020

A Chi-square test was conducted to examine the association between the type of program (Modular vs. Non-Modular) and employment status. The results showed a statistically significant relationship between the two variables, χ^2 (5) = 13.37, p = 0.020. Since the p-value was less than the threshold of 0.05, the null hypothesis, which stated that there was no relationship between program type and employment status, was rejected. This finding suggests that the type of program (Modular vs. Non-Modular) had a significant impact on participants' employment status. A multivariate analysis utilizing a multinomial logistic regression was performed to establish this relationship.

4.4.5 Multinomial Logistic Regression of Nature of Course and Employment Status

A Multinomial logistic regression analysis with relative risk ratios (RRR) was utilised. The outcome categorical outcome was employment category that included; being employed in a different field of study, employed in own field of study, self-employed in a different field of study, self-employed in the same field of study, and being unemployed. Unemployed was used as the base/reference category in this analysis.

Table 4.9 Multinomial Logistic Regression of Nature of Course on Employment Category

EmployCat	**Employed_Diff Field**		**Employed_ Own Field**		**Self-Employed_Diff field**		**Self-Employed_ Own Field**		**In training**	
	RRR	P>z	RRR	P>z	RRR	P>z	RRR	P>z	RRR	P>z
Nature_of_Course	0.4967	**0.039**	0.4815	**0.015**	0.5743	0.083	0.5272	0.052	0.2243	0.071
Spell Duration	1.0946	**0.000**	1.1091	**0.000**	1.1225	**0.000**	1.1116	**0.000**	0.7725	0.120
Application8WKS	1.1492	**0.033**	1.2743	**0.000**	1.2793	**0.000**	1.3351	**0.000**	0.5068	0.289
migration_TO	1.7028	**0.025**	1.8473	**0.005**	1.4345	0.116	1.5834	**0.048**	0.9277	0.701
reservation_wage2	1.0004	**0.000**	1.0004	**0.000**	1.0004	**0.000**	1.0004	**0.000**	0.0727	0.234
jsi	1.9438	**0.000**	1.3969	**0.043**	1.8952	**0.000**	1.3177	0.128	1.8225	0.115
Gender	1.4212	0.274	1.6915	0.069	1.4432	0.230	1.8728	**0.050**	1.0932	0.230
CourseDuration	0.9733	0.084	0.9627	**0.003**	0.9882	0.399	0.9830	0.216	0.6382	0.399
AcadQual	1.1206	0.588	1.5206	**0.028**	1.0498	0.811	1.1031	0.636	0.6998	0.811
_cons	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Unemployed	(Base outcome)									

Based on the analysis, the predictor Nature of Course and control variables; Spell Duration, Application8WKS, migration_TO, reservation_wage2, JSI, Gender, Course Duration, and Academic Qualification (AcadQual) were statistically significant on **“employment in a different field”** with p-values less than 0.05. Specifically, the variable "Nature_of_Course" had a Relative Risk Ratio (RRR) of 0.4967 and a p-value of 0.039, suggesting that respondents who pursued non-modular programs had a 50.5% lower relative risk of being employed in a different field compared to those who were unemployed.

Each additional year of unemployment (Spell Duration), increased the likelihood of finding employment in a different field by 9% compared to those unemployed (RRR = 1.0946, p = 0.000). Similarly, each additional application submitted (Application8WKS) was associated with a 14.9% higher relative risk of finding employment in a different field compared to being unemployed (RRR = 1.1492, p = 0.000). Respondents who migrated (migration_TO) had a 70.28% higher chance of finding employment in a different field compared to those who did not migrate (RRR = 1.7028, p = 0.025).

High job search intensity compared to low job search intensity was associated with a 94.38% higher chance of finding employment in a different field (RRR = 1.9438, p = 0.000). The reservation wage (reservation_wage2) had a marginal effect, showing a slight increase in the relative risk of finding employment in a different field (RRR = 1.0004, p = 0.000).

For the **"Employed in my Field of Study"** category, the nature of the course was statistically significant (RRR= 0.4815, P= 0.015). This suggested that that respondents who pursued non-modular programs had a 48.15% lower relative risk of being employed in a same field of study compared to those who were unemployed. Other significant control variables included; Spell Duration, Application8WKS, migration_TO, reservation_wage2, jsi, Gender, Course Duration, and Academic Qualification (AcadQual).

Controlling for SpellDuration, an increase by one month in a job search, the relative risk for finding employment in own field increased by 10.91% other variables in the model held constant. The number of applications (Application8WKS) was statistically significant (RRR= 1.2743, p= 0.000). Increasing the number of applications by one, the relative risk for finding employment in own field of study compared to being unemployed increased by 27.43% other variables held constant. For respondents who migrated(migration_TO), relative to those who did not migrate, the relative risk for finding employment in their own field of study compared to unemployment increased by 84.73% (RRR= 1.8473, p= 0.000).

Further, an increase in the reservation wage by one shilling, the relative risk for finding employment in one's own field of study to unemployment was statistically significant but very marginal (RRR= 1.0004, p = 0.000). The job search intensity significantly affected employment in one's own field (RRR=1.1369, p = 0.043). For high job search intensity relative to low job search intensity, the relative risk for finding employment in own field of study to unemployment increased by 39.69 % given the other variables in the model were held constant (RRR=1.3969, p= 0.043).

In addition, a one-year increase in the course duration, the relative risk for finding employment in one's field of study compared to unemployment decreased by 3.7%. (RRR= 0.9627, p = 0.003). Academic qualifications significantly affected employment in one's field of study (RRR= 1.5201, p = 0.028). For respondents who had higher academic qualifications relative to artisan qualifications, the relative risk for finding employment in one's own field of study to unemployment increased by 52.01% other variables held constant. Other variables such as gender, marital status, age, education sponsor, and exam grade did not influence one's probability of being employed in one's field of study.

For the "**Self-Employed in a Different Field of Study**" the nature of the course was not statistically significant (RRR= 0.5743, P= 0.083). Controlling for "Spellduration“, the results were statistically significant (RRR=1.1225, p =0.000). By Increasing the spell duration by one month, the relative risk for finding "self-employment in different field of study" to unemployment increased by 12.25%, other variables held constant. Additionally, increasing the number of applications by 1, the relative risk for finding employment in one's own field to unemployment increased 27.93%. Reservation wage had a minimal effect on the likelihood of employment in a different field of study compared to being unemployed although this was statistically significant (RRR= 1.0004, p = 0.000). Finally, high job search intensity relative to low job search intensity had a relative risk of finding a job in a different field of study compared to unemployed of 89.52%.

In the "**Self-Employed in Field of study**" category, the nature of the course was not statistically significant (RRR= 0.5272, P= 0.052)- non-modular programmes relative to modular programmes, the relative risk for finding employment in own field of study to unemployment decreased by a factor of 0.5272. However, there were control variables that explained the relationship between the nature of the course and Self-Employed in Field of study.

Specifically, increasing the spell duration (Spell Duration) by one month, the relative risk for finding employment in their own field to unemployment increased by 11.16%. The number of applications (Application8WKS) was statistically significant (RRR= 1.3351, p= 0.000). Increasing the number of applications by one, the relative risk for finding employment in own field of study to unemployment increased by 33.51% other variables held constant. Further, geographical mobility(migrationTo) was statistically significant (RRR=1.5834, p= 0.048). The relative risk of finding self-employment in own field of study to unemployment increased by 58.34%, other variables held constant.

Gender was significant variable (RRR= 1.8728, p= 0.50) suggesting that being male increased the likelihood of self-employment in the one’s field by 87.28. on the other hand, Reservation wage had a marginal effect on self-employment in one’s field.

4.4.5.1 Diagnostic Tests

In testing the multinomial logistic regression model in Stata, various diagnostic tests were employed to ensure its validity. The assessments included checking the Independence of Irrelevant Alternatives (IIA), goodness-of-fit, multicollinearity, outliers, and model specification. These tests were crucial in identifying and addressing potential issues, which helped improve the robustness of the analysis. Each diagnostic test offered unique insights into the model's performance and reliability, and conducting these tests comprehensively was essential for achieving accurate and reliable results. Table 4.10 gives summary diagnostic tests.

Table 4.10 Diagnostic Tests for Multinomial Regression of Nature of Course on Employment Status

	Coefficients			
	M1	**M2**	**Difference**	**Std.err.**
Independent Irrelevant Alternative test				
Nature of Course	-0.0235834	0.088411	-0.1119943	0.091
Test of H0: Difference in coefficients not systematic				
chi2(1) = (b-B)'[(V_b-V_B)^(-1)](b-B)				
= 1.52				
Prob > chi2 = 0.2177				
Goodness-of-fit test				
Dependent variable: EmployCat				
chi-squared statistic = 42.316				
degrees of freedom = 40				
Prob > chi-squared = 0.371				

The Hausman test compared the coefficients from models M1 and M2 to assess if they differed systematically for the composite outcome variable employment category in measuring the independent irrelevant alternative. The test indicated that the difference in coefficients for the variable Nature of Course was not statistically significant, (χ^2(6, 1463) = 1.52, p= 0.2177 suggesting that there was no systematic difference between the coefficients of the models. This implied that the choice of the reference category did not negatively impact on the outcome. The goodness-of-fit test for the multinomial logistic regression model, assessed the model's fit to the data. The chi-squared statistic was statistically significant ($\chi^2(6, 1463) = 42.32$, p= 0.37 suggesting that the model adequately fit the data. Following the diagnostic tests, the model was deemed fit for further analysis.

Hypothesis testing

The null hypothesis for this sub hypothesis was;

$H_0 1(b)$: The nature of STEM academic programs has no statistically significant effect on employment status of graduates of national polytechnics in Kenya.

The study rejected the null hypothesis at $\propto = 0.05$ and concluded that the nature of STEM academic program has a statistically significant effect on employment status of graduates of national polytechnics in Kenya.

The contingency table revealed that the distribution of respondents across employment statuses differed between Modular and Non-Modular participants. For example, a higher percentage of those in Modular programs were employed compared to those in non-modular programs. The expected frequencies, assuming no association between program type and employment status, were provided alongside the observed counts, highlighting the discrepancies that contributed to the Chi-square statistic. These results supported the conclusion that program type significantly influenced employment outcomes.

Smith & Brown, (2018) indicate that respondents who undertook non-modular courses exhibited slightly lower employment rates compared to those who pursued modular courses. The significance of this difference underscores the potential influence of course structure on labour market outcomes, suggesting that modular programs may offer advantages in facilitating employment opportunities for TVET students. These findings provide empirical evidence supporting the association between course type and employment rates, informing discussions on the effectiveness of different instructional approaches in preparing students for the workforce. A further analysis was performed through a multinomial logistic model to establish the magnitude of the predictors on employment category.

They further argued that young people do not have strong networks and that is why social capital did not play a significant role in determining ones' employment status. Participants highlighted that gender was an important aspect particularly in a male dominated field. They stressed the need for affirmative action to increase the employment of female technicians and technology in STEM field as this could help reduce gender disparities and promote diversity in taking equal fields. The group believed that for graduates, finding a job was more dependent on proactive job searching, being open to relocation and addressing gender imbalances rather than relying solid on demographic factors or academic achievements

In summary, this analysis highlights several significant factors that influence different employment outcomes compared to being unemployed. Migration patterns increased the probability of finding employment. Respondents who migrated showed positive employment outcomes compared with those who did not. Additionally, job search intensity was a significant determinant of employment outcome. Respondents with a higher job search intensity showed higher employment outcomes. TVET graduates should consider making more job applications to find job placements. The minimum wage rate acceptable for one to take up a job offer had a marginal effect across the four types of job statuses. Considering the time of the study, most respondents were prospective young employees who had just graduated from TVET institutions and therefore did not have strong bargaining power. This explained why the reservation wage rate was marginally significant. Other variables did not indicate significant determinants of employment status. These included; Age, marital status, gender, course advancement, social capital, and exam grade.

During the **focus group discussion (FGD),** participants strongly argued that

"*The findings suggest the importance of practical skills and personal attributes in securing employment within one's field of study especially for technical courses. Employers especially in the private sector prioritize hands on experience and practical competencies over academic qualifications. Job seekers have to demonstrate mastery of skills and confidence in one's ability in order to secure employment. Additionally, it is not just about what one knows but how effective one can apply that knowledge in real world situations that truly determines employment success.*"

During the FGD, participants agreed that;

"*Migration patterns significantly influenced employment outcomes with those who migrated generally finding job opportunities compared to those who did not move. Relocating often opens new networks and access to more diverse job markets thereby increasing the likelihood of finding employment. In addition, actively seeking multiple opportunities was crucial for securing employment*".

D'Amuri and Peri (2015) found out that migration often results in overqualification and job mismatches, leading to suboptimal employment outcomes. In contrast, (Dumont et al.,

2010) support the finding that migration enhances employment prospects by showing that migrants achieve better job matches and higher employment rates due to increased labour mobility. The study findings concur with these findings. Results have revealed that graduates who migrated especially from rural to urban areas had a higher probability of finding employment. Similarly, Caliendo & Schmidl (2016) agree that job search intensity is beneficial, demonstrating that proactive job searching improves employment outcomes. Card et al., (2015), resonate with the current findings that a higher number of job applications positively correlates with employment, suggesting that more applications may lead to better employment outcomes. In addition, Card et al., (2015), found out that intensive job search efforts, including submitting more job applications, improve employment outcomes. These findings agree with the current study.

The nature of a course—whether modular or non-modular—can significantly influence employment outcomes, including the duration of unemployment and employment status. Modular courses, which are typically organized into discrete units or modules that can be completed individually or flexibly, offer a unique approach to education compared to traditional non-modular courses, which follow a more rigid, sequential structure. Research indicates that modular courses can affect the adaptability and employability of graduates in various ways. For instance, modular courses often allow students to gain specific skills that are highly relevant to current job market demands, potentially leading to shorter unemployment durations (Lusher et al., 2021; Glover et al., 2022). Modular courses often emphasize practical skills and competencies, which can make graduates more attractive to employers and thus reduce the time needed to secure employment (Kim et al., 2023). On the other hand, non-modular courses, which usually provide a comprehensive, in-depth education over a fixed period, might offer a more holistic understanding of a subject but may not always align with specific job market needs. Graduates from non-modular programs might face longer unemployment durations if their education does not directly correspond to immediate job market demands or if they lack the specific skills sought by employers (Brown & Hesketh, 2019; McGrath & Yamada, 2023). For example, non-modular courses in traditional disciplines might not always integrate practical skills or industry-specific knowledge, potentially impacting the speed at which graduates find relevant employment (William et al., 2022)

4.4.6 Nature of Course and Sector Employed

The third sub hypothesis of the first objective was to establish the effect of nature of course on the sector of employment of graduates of national polytechnics in Kenya. The descriptive statistics are shown in table 4.11

Descriptives Statistics

Table 4.11: Distribution of Data

Nature of Course	Sector of Employment		Total
	Private	Public	
Modular	88(19%)	76(16%)	164(35%)
Modular	163(35%)	140(46%)	303(65%)
Total	251(54%)	216(46%)	467(100%)

The table show that there was a total of 467 respondents who were employed in both public and private sectors. A total of 251 were employed the private sector while 216 were employed in the public sector. There were 251(54%) of respondents were employed in the private sector and 216(46%) in the public sector. Table 4.12 gives a pairwise correlation between the nature of the course and the sector employed of respondents.

Table 4.12 Correlation between Nature of Course and Sector Employed.

Nature_of_Course		**Sector**
Nature_of_Course	1.000	
	1473	
Sector	-0.0013	1.000
	467	467

The table shows the Pearson correlation between "Nature_of_Course" and "Sector," with a value of -0.0013, $p<0.05$, suggesting that it was statistically significant. The number of observations for "Nature_of_Course" is 1,473, while for "Sector" it is 467. This necessitated a further multivariate analysis using a binary logistic regression model.

Table 4.13 Binary Logistic Regression of Nature of Course and Sector of Employment

Logistic regression				**Number of obs =**	**467**	
Private Sector	**Odds ratio**	**Std. err.**	**Z**	**P>z**	**[95% conf. interval]**	
Nature_of_Course	1.004	0.203	0.02	0.981	.6756	1.494
EmployCat	.5840	0.107	-2.93	0.003	.407	.837
Examgrade	1.226	0.087	2.86	0.004	1.066	1.409
Marital_Status	1.556	0.325	2.11	0.035	1.032	2.345
A10_Age	.931	0.031	-2.08	0.038	.871	.995
_cons	5.77	7.181	1.41	0.159	.504	66.103
Public Sector (Base outcome)						

Note: LR chi2(5) = 34.82, Prob > chi2 = 0.0000, Pseudo R2 = 0.0540, Log likelihood = -305.12224

In the logistic regression analysis (Table 4.13), Nature of Course was examined as the primary predictor of employment in the private sector, with the public sector as the reference category. The odds ratio for Nature of Course was not statistically significant (OR=1.004, $p = 0.981$). This result might suggest that the nature of the course did not have a meaningful impact on the likelihood of being employed in the private sector relative to the public sector, suggesting that course type was not a significant factor in determining sector employment. Muralidharan, K. (2015

Among the control variables, several variables showed significant effects on the probability of private sector employment. Exam Grade had an odds ratio of 1.226 (p-value

= 0.004), indicating that higher exam grades were associated with increased odds of being employed in the private sector. Marital Status also had a significant impact, with an odds ratio of 1.556 (p-value = 0.035), suggesting that married respondents had higher odds of working in the private sector compared to those in the public sector. Age, with an odds ratio of 0.932 (p-value = 0.038), was significantly associated with decreased odds of private sector employment, implying that older respondents were less likely to be employed in the private sector. The Employment Category variable had an odds ratio of 0.584 (p-value = 0.003), which indicates that certain employment categories were associated with lower odds of private sector employment relative to the public sector.

The analysis of TVET graduates' employment outcomes showed that while the type of course completed does not significantly influence whether graduates work in the public or private sector, factors such as employment category and academic performance were key determinants. Specifically, graduates' sectoral placement was more strongly associated with their employment category and exam grades than with the nature of their training. Additionally, marital status positively affected the likelihood of securing employment, likely due to perceptions of stability, whereas age negatively impacted sectoral placement, suggesting that older graduates faced more challenges. These results underscore the importance of employment category, academic performance, and personal characteristics in determining whether TVET graduates find jobs in the public or private sector.

Table 4.14 : Diagnostic Tests of the Binary Logistic Model of Sector Employment and Employment Category.

Diagnostic Tests						**Number of obs**	**460**
						LR chi2(2)	43.21
						Prob > chi2	0
Log likelihood = -296.38773						Pseudo R2	0.0679
Goodness-of-fit test after logistic model							
Hosmer–Lemeshow chi2(8) =		2.55					
Prob > chi2 =		0.9591					
Sensitivity		Pr(+ D)	71.72%				
Specificity		Pr(-~D)	56.02%				
Correctly classified			64.35%				
Linktest results							
SectorEmpl	Coefficient	Std. err.	z	P>z		[95% conf.	interval]
_hat	1.031	0.17487	5.9	.000		0.6882	1.3737
_hatsq	-.099844	0.19835	-0.5	0.615		-0.4886	0.2889
_cons	.034171	0.12054	0.28	0.777		-0.2021	0.2704
Pearson Chi-Square Test							
Pearson chi2(444) =		462.38					
Prob > chi2 =		0.2641					

In evaluating the logistic regression model for predicting SectorEmpl, several diagnostic tests revealed its performance. The Hosmer-Lemeshow test suggested that the observed and expected event rates were well-aligned ($\chi^2(1, 807) = 0.2.55$, p= 0.9591. The classification table demonstrated a sensitivity of 71.72% and specificity of 56.02%, with a correct classification rate of 64.35%, suggesting moderate predictive accuracy. The linktest results showed that the model's predicted probabilities (_hat) were significant and well fitted. Lastly, the Pearson chi-square test suggested a statistic of no significant discrepancy between observed and expected frequencies ($\chi^2(1, 807) = 0.462.38$, p= 0.2641. Overall, these diagnostics collectively indicated that the model fitted the data reasonably well. This formed sufficient ground for a binary logistic regression analysis shown in table 4.19

Hypothesis Testing

The null hypothesis for this sub hypothesis was;

$H_0$1(c): The nature of STEM academic programs has no statistically significant effect on Sector of employment of graduates of national polytechnics in Kenya. The study did not rejected the null hypothesis at $\propto = 0.05$ and concluded that the nature of STEM academic program had no statistically significant effect on Sector of employment of graduates of national polytechnics in Kenya.

Industry experience, internships, and professional networks are more decisive in securing private sector jobs (Seligman et al., 2018; Lippman & Sheehan, 2020). The broad categorization of courses in this study may further dilute the impact of specific course types, making it difficult to discern a meaningful relationship between course nature and employment sector. Other studies argue that, without considering these confounding factors, course type may appear insignificant, though it may still indirectly influence sector preferences (Dahl et al., 2019; Roberts & Weeden, 2018).

Further, in the context of modular versus non-modular programs, this could imply that the structure or flexibility of the program itself does not strongly determine sector-specific employment outcomes. Muralidharan (2015) suggests that other factors, such as the overall skill set acquired, networking opportunities, or industry demand, might play a larger role in influencing employment decisions than the format of the educational program. Similarly, Farole et al. (2017) emphasize that regional labor market conditions and broader economic factors, rather than educational structure alone, are more influential in determining sector employment outcomes. Therefore, while the nature of the course could be expected to have some effect on sector-specific employment, the data suggests that the impact might be minimal, especially in sectors where transferable skills and practical experience are more highly valued.

Contrarily, there are substantial arguments against these findings. Specific fields, such as business, IT, and engineering, are generally linked to private sector jobs, while public administration and social sciences tend to align with the public sector (Roberts & Weeden, 2018; Feldman, 2020). The lack of statistical significance in this study might reflect unaccounted-for factors, such as socio-economic background, location, or sector-specific skills, which could overshadow the influence of course type on employment outcomes (Tymon, 2013; Feldman, 2020). Additionally, it's possible that the sample size or scope of the study limited the ability to detect a true effect, suggesting that future research should explore this relationship with more targeted variables to better understand how course nature impacts employment in different sectors.

4.4.7 Nature of Course and Unemployment Spell

The final analysis of this first objective was to analyse the nature of STEM academic on the unemployment duration of graduates of national polytechnic using the survival approach model. This analysis sought to establish the time it takes (in months) for TVET graduates to find employment (time to event). The analysis used parametric tests to model these survival functions. Results of the analysis were compared and conclusions made. The predictor variable was the nature of the course- Modular versus non-modular. Other control variables included; Applications8weeks, MigrateTo, Gender, A10: Age, jsi, EducSponsor, Reservation wage, Highest Qualification, and Exam Grade and year of graduation.

4.4.7.1 Description of Survival Data

The median time to employment described the average survival time to employment of respondents.

Table 4:15 Median Survival Probability

Nature of course	Time at risk	Incidence rate	Number of Subjects	------ Survival time…. 25%	50%	75%
Modular	25,334.36	0.01993	869	15.05	34.95	.
Non- Modular	20,508.85	0.01399	589	24	49.93	65.93
Total	45,843.21	0.01728	1458	18.03	37.97	65.93

The median time to employment at 95%CI for the nature of the course was computed (Table 4.15). It was estimated that a graduate of a modular program had a median time to employment of 34.95 months (95%CI: 33.2025 -36.6975) while the non-modular programs was 49.93 months((95%CI:47.43-52.43). This implied that 50% of graduates who pursued modular programs stayed for 34.95 months before employment. Similarly, 50% of non-modular graduates took an average of 49.93 months before employment.

Two Sample T-TEST FOR Modular and Non-Modular Programs and on Unemployment Duration

Table 4.16

Nature of Course	Obs	Mean	Std.err	Std dev
Non- Modular	594	34.49	0.77	18.87
Modular	879	28.78	0.57	16.93
Combined	1,473	31.09	0.47	17.95
diff		5.71	0.94	

Note. The non-modular group had a higher mean (34.49 months) compared to the modular group (28.78 months), with a difference of 5.71 months. There was a statistically significant difference in unemployment duration for the two types of programs t (1471) = 6.06, p< 0.001.

Following the bivariate analysis, the study further analysed the time to event(employment) using parametric tests that included; Weibull, exponential, and Gompertz models,

4.4.7.2 Parametric Tests

Parametric tests, including the Weibull, exponential, and Gompertz models, were used to analyse the unemployment spell, with the nature of the course as the predictor variable. These tests made specific assumptions about the distribution of the data and aimed to evaluate hypotheses and make inferences about the relationship between the unemployment spell and the nature of the course. These parametric models were employed to determine whether they provided greater statistical power and precision on the model. The coefficients for the various models were computed to establish the model with the least BIC and AIC. The model with the best fit(least value) was selected.

Table 4.17 Parametric Regression Model Coefficients

Variable	Gompertz				Weibull				Exponential			
_t	Coefficient	Std. err.	z	P>z	Coefficient	Std. err.	z	P>z	Coeff.	Std. err.	z	P>z
Nature_of_Course												
Non Modular	-0.144	0.077	-1.87	0.049	-0.150	0.077	-1.95	0.050	-0.145	0.077	-1.88	0.048
Gender												
Male	0.126	0.077	1.64	0.101	0.126	0.077	1.65	0.099	0.126	0.077	1.64	0.100
CourseDuration	0.026	0.004	6.39	0.000	0.032	0.004	7.66	0.000	0.024	0.004	6.14	0.000
ReservationWage2	0.000	0.000	3.93	0.000	0.000	0.000	4.15	0.000	0.000	0.000	3.83	0.000
Application_8WKS	0.139	0.013	10.36	0.000	0.146	0.013	10.9	0.000	0.137	0.013	10.21	0.000
jsi												
High jsi	0.214	0.083	2.59	0.010	0.220	0.083	2.66	0.008	0.213	0.083	2.58	0.010
Migration_Dummy												
Migrated	0.182	0.078	2.32	0.020	0.194	0.078	2.48	0.013	0.178	0.078	2.27	0.023
A10_Age	0.022	0.012	1.92	0.050	0.022	0.012	1.9	0.049	0.022	0.012	1.92	0.490
Examgrade												
Distinction	0.094	0.189	0.5	0.618	0.102	0.189	0.54	0.589	0.091	0.189	0.48	0.628
Fail	-0.252	0.122	-2.07	0.039	-0.246	0.122	-2.01	0.045	-0.253	0.122	-2.08	0.038
Pass	-0.014	0.084	-0.16	0.869	-0.004	0.084	-0.05	0.959	-0.017	0.084	-0.2	0.843
Refer	-0.138	0.208	-0.66	0.507	-0.136	0.208	-0.65	0.513	-0.138	0.208	-0.66	0.506
Year_Completion(2017 Base)												
2018	0.133	0.148	0.900	0.369	0.128	0.148	0.87	0.386	0.142	0.147444	0.970	0.334
2019	0.576	0.207	2.780	0.005	0.486	0.206	2.36	**0.018**	0.493	0.205782	2.400	0.017
_cons	-7.067	0.487	-14.5	0.000	-7.496	0.470	-15.95	0.000	-6.726	0.455	-14.8	0.000
/ln_p/gamma	0.067	0.033	2.04	0.041	0.019	0.003	7.07	0.000				
p	1.069	0.035										
1/p	0.936	0.030										

Table 4.18 Model Selection Indices Using Parametric Distributions

Model	**N**	**ll(null)**	**ll(model)**	**df**	**AIC**	**BIC**
Gompertz	1,459	-1936.6	-1830.159	15	**3690.3**	**3770**
Weibull	1,459	-1943	-1852.831	15	3735.7	3815
Exponential	1,459	-1943.2	-1854.861	14	3737.7	3812

Model selection from candidate variables was accomplished by minimization of the Akaike and Bayesian information criteria (AIC and BIC). The Gompertz regression distribution was preferred based on the minimum values of Akaike and Bayesian information criteria (AIC and BIC), (Akaike, 1974 1998; Cavanaugh & Neath, 2019; Schwarz, 1978; Zhang et al.)

4.4.7.4 Gompertz Hazard Ratios

The table 4.19 gives the Gompertz hazard ratios

Table 4.19 Gomperts Hazard Ratios

_t	Haz. ratio	Std. err.	z	P>z
Nature_of_Course				
Non Modular	0.878	0.068	-1.670	0.049
Gender				
Male	1.142	0.088	1.740	0.083
CourseDuration	1.019	0.006	3.180	0.001
ReservationWage2	1.000	0.000	5.110	0.000
Application_8WKS	1.172	0.016	11.430	0.000
jsi				
medium jsi	0.996	0.093	-0.040	0.965
High jsi	1.256	0.104	2.750	0.006
Migration_Dummy				
Migrated	1.207	0.095	2.390	0.017
A10_Age	1.024	0.012	2.050	0.040
Examgrade				
Distinction	1.115	0.211	0.580	0.564
Fail	0.754	0.094	-2.270	0.023
Pass	0.974	0.082	-0.320	0.750
Refer	0.852	0.177	-0.770	0.441
Year_Completion				
2018	1.142	0.169	0.900	0.369
2019	1.780	0.368	2.780	0.005
_cons	0.000	0.000	-15.860	0.000
/gamma	0.021	0.003	7.420	0.000

The model provided a significant improvement over a null model with no predictors ($\chi 2(22, N=1473) = 113.98$, $p< 0.001$). The log- likelihood of the fitted model was -1857.2734. The hazard ratios derived from the Gompertz proportional hazards regression model provided insights into the factors influencing the time to employment.

The findings suggested that graduates from non-modular programs had a 12.2% lower hazard of finding employment compared to those from modular programs (HR = 0.878, P= 0.049). This implied that modular courses were associated with a faster time to employment, potentially due to their structure being more aligned with job market needs or providing better preparation. Each additional unit increase in course duration was associated with a 1.9% higher hazard of finding employment ($HR = 1.019$, $p < 0.001$). Findings further showed that every shilling increase in reservation wage had a negligible but significant increase in the hazard of finding employment ($HR=1.000$, $p < 0.001$). Further, each additional job application submitted within the first eight weeks increased the hazard of finding employment by 17.2% ($HR = 1.172$, $p < 0.001$). Graduates with high job search intensity had a 25.6% higher hazard of finding employment compared to those with low intensity ($HR = 1.256$, $P < 0.001$).

Migrants had a 20.7% higher hazard of finding employment compared to non-migrants ($HR = 1.207$, $p < 0.05$). Each additional year of age was associated with a 2.4% higher hazard of finding employment ($HR = 1.024$, $p < 0.05$). Respondents who failed an exam had a 24.6% lower hazard of finding employment compared to those who passed ($HR = 0.754$, $p = 0.023$). The 2018 year of completion did not have a substantial impact on the time to employment compared to 2017($hr = 1.142$, $p > 0.05$). The 2019 year of completion had a substantial impact on the time to employment compared to 2017($hr = 1.78$, $p < 0.05$).

4.4.7.5 Model Estimation using the Gomperts Regression Coefficients.

Table 4:20 Model Estimation using the Gomperts Regression Coefficients.

Gompertz **_t**	**Gompertz** **Coefficient**	**Std. err.**	**z**	**P>z**
Nature_of_Course				
Non Modular	-0.144	0.077	-1.87	0.049
Gender				
Male	0.126	0.077	1.64	0.101
CourseDuration	0.026	0.004	6.39	0.000
ReservationWage2	0.000	0.000	3.93	0.000
Application_8WKS	0.139	0.013	10.36	0.000
jsi				
High jsi	0.214	0.083	2.59	0.010
Migration_Dummy				
Migrated	0.182	0.078	2.32	0.020
A10_Age	0.022	0.012	1.92	0.050
Examgrade				
Distinction	0.094	0.189	0.5	0.618
Fail	-0.252	0.122	-2.07	0.039
Pass	-0.014	0.084	-0.16	0.869
Refer	-0.138	0.208	-0.66	0.507
Year_Completion(2017 Base)				
2018	0.133	0.148	0.900	0.369
2019	0.576	0.207	2.780	0.005
_cons	-7.067	0.487	-14.5	0.000
/ln_p/gamma	0.067	0.033	2.04	0.041
p	1.069	0.035		
1/p	0.936	0.030		

The hazard function $\lambda(t)$ is given by:

$$\lambda(t)=\lambda_0 \exp(\gamma t)\exp(X\beta)$$

where:

$\lambda(t)$ is the hazard rate at time

λ_0 is the baseline hazard function.

γ is the Gompertz shape parameter.

X is the vector of covariates.

β is the vector of coefficients for the covariates.

The model investigated the relationship of predictors and the time-to-event(employment) through the hazard function. The predictor had a Gompertz distribution.

The general hazard function was given by:

$$\lambda(t|X) = \lambda_0 \exp(\gamma t)\exp(X\beta) \qquad (1)$$

The baseline survival function was estimated by setting all predictors to zero. The resulting baseline survival function Surv(0) is;

$$\text{Surve}\ (0) = \lambda(t|X) = \lambda_0(\gamma t)e^0 = \lambda_0\ (t) \qquad (2)$$

The cumulative hazard function $H(t)$ is the integral of the hazard function over time:

$$H(t|X) = \int_0^t \lambda(u \mid X)du \qquad (3)$$

The Gompertz model can be expressed as:

$$H(t|X) = \frac{\lambda 0}{\gamma}(\exp(\gamma t)-1)\exp(X\beta) \qquad (4)$$

The survival function S(t|X) is obtained from the cumulative hazard function H(t|X) using the formula:

$$S(t|X) = \exp(-H(t|X)) \qquad (5)$$

Substitute H(t|X) into this formula to get:

$$S(t|X) = \exp(-\frac{\lambda 0}{\gamma}(\exp(\gamma t)-1)\exp(X\beta) \qquad (6)$$

Estimating the Survival Function

Significant predictor variables in the model were; i. Nature of Course, Applications8wks, Applications4wks, CourseDuration, Migration_Dummy and jsi. A model estimation with the following hypothetical parameters was performed. The Cox regression coefficients utilizing the Breslow method for handling ties, explored the relationship between various predictors and the survival function given that the respondents were employed within the 65 months of the study.

Assume a graduate had done a non-modular program (Nature of Course), made 10 applications in the last 8 weeks (Applications8wks), had 3 years course duration (CourseDuration) with high job search intensity(jsi= High, migrated(Migration dummy=1), Failed exam(Exam = 3)and completed in 2019.

Given the computed coefficients from table 4.33, the resulting hazard function will be given by;

Estimate1= Surv(0) =

NOC_NonModular1=surv00^exp((-0.130Non Modular + 0.019CourseDuration + 0.0000202ReservationWage + 0.228Highjsi + 0.18Migrated+ 0.024Age - 0.282FailExam+0.5722019Year of Graduation))……………………………………(7)

Where NOC is the Nature of the Course.

This becomes:

NOC_NonModular1=surv00^exp((-0.130+3*0.019+10000*0.0000202+0.228+ 0.188+ 30*0.024-0.282+0.57))…………………………………………………………(8)

Assume further that a graduate pursued a modular program with the same parameters as earlier hypothesized. The resulting survival function would be:

NOC_Modular1=surv00^exp ((0.019CourseDuration + 0.0000202ReservationWage + 0.228Highjsi + 0.18Migrated+ 0.024Age -0.282FailExam+0.5722019Year of Graduation))…………………………………………………………………………….(9)

Replacing the Xi Variables with the specific predictors and omitting the nature of course coefficient, the equation becomes;

NOC_NonModular1= surv00^exp ((3*0.019+10000*0.0000202+0.228+ 0.188+ 30*0.024-0.282+0.57))………………………………………..…………………(10)

The resulting survival model is shown in the figure 4:2.

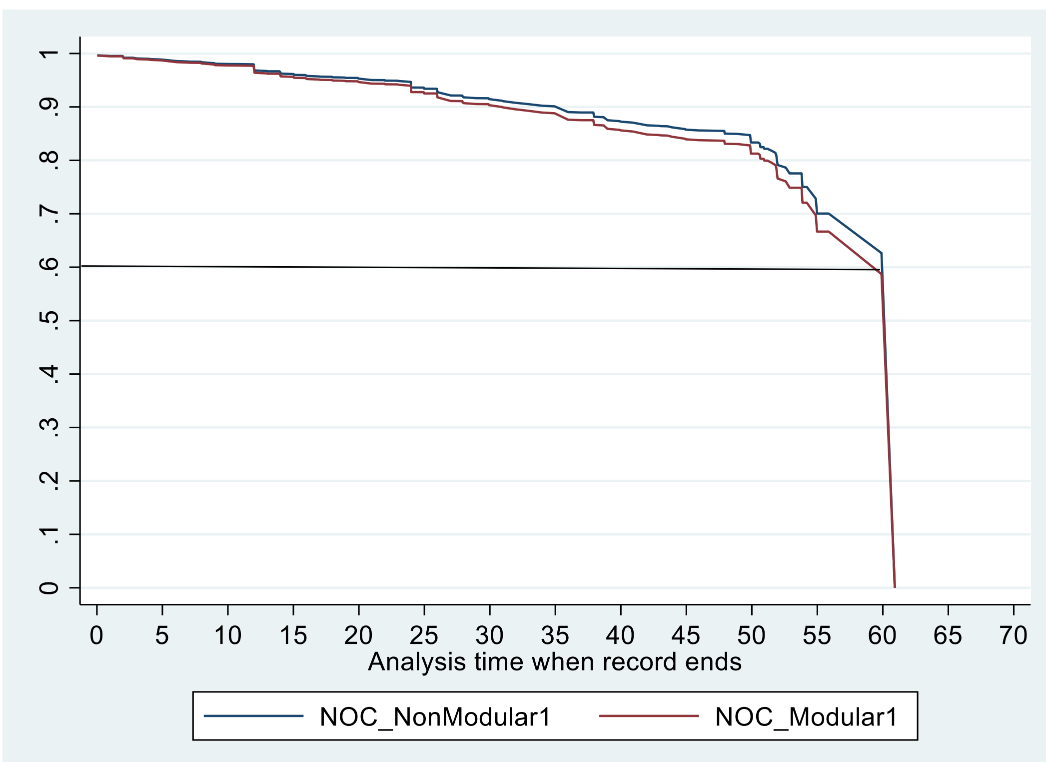

Figure 4:2 Analysis Time When Records Ends

The survival curve for the analysis shows a decline from left to right, indicating that the survival probability decreased over time. Specifically, the survival probability dropping to approximately 0.6 suggested that, as time progressed, about 60% of respondents remained in the non-failure/Unemployed or "surviving" state. This decline reflects the cumulative occurrence of time to employment. The survival curve revealed how different educational pathways impacted the time to event(employment). Censoring: A steep drop shows high number of censored observations when the study time ended.

4.4.7.6 Model Adequacy Checking

Model adequacy checking involved evaluating the statistical model to ensure it accurately represented the underlying data and met the assumptions necessary for reliable predictions and inferences. A Schoenfeld residual test was performed.

Table 4.21 Schoenfeld Residual Test

Variable	rho	chi2	Df	Prob>chi2
Nature_of Course			1	
Non-Modular	0.01814	0.15	1	0.6944
Gender	-0.01627	0.12	1	0.7273
Reservatiowage2	0.28107	171.86	1	0.0000
A25_Application8weeks	-0.03479	0.67	1	0.4130
Jsi			1	
Medium jsi	-0.0222	0.23	1	0.6322
High jsi	0.06878	2.24	1	0.1349
Examgrade			1	
Credit	-0.03949	0.73	1	0.3924
Distinction	0.06441	1.9	1	0.1677
Fail	0.02798	0.36	1	0.5497
Marital_Status	0.03455	0.56	1	0.4532
Global test		185.98	11	0.0610

The Schoenfeld residual test assessed the proportional hazards assumption in the Cox regression model. A non-significant global test p-value (p= 0.0610) suggested no strong evidence against the proportional hazards assumption for all the predictors tested except for "Reservation2". This implied that the relationship between the predictors and time remained relatively constant over time, which was in line with the assumptions of the Cox proportional hazards model.

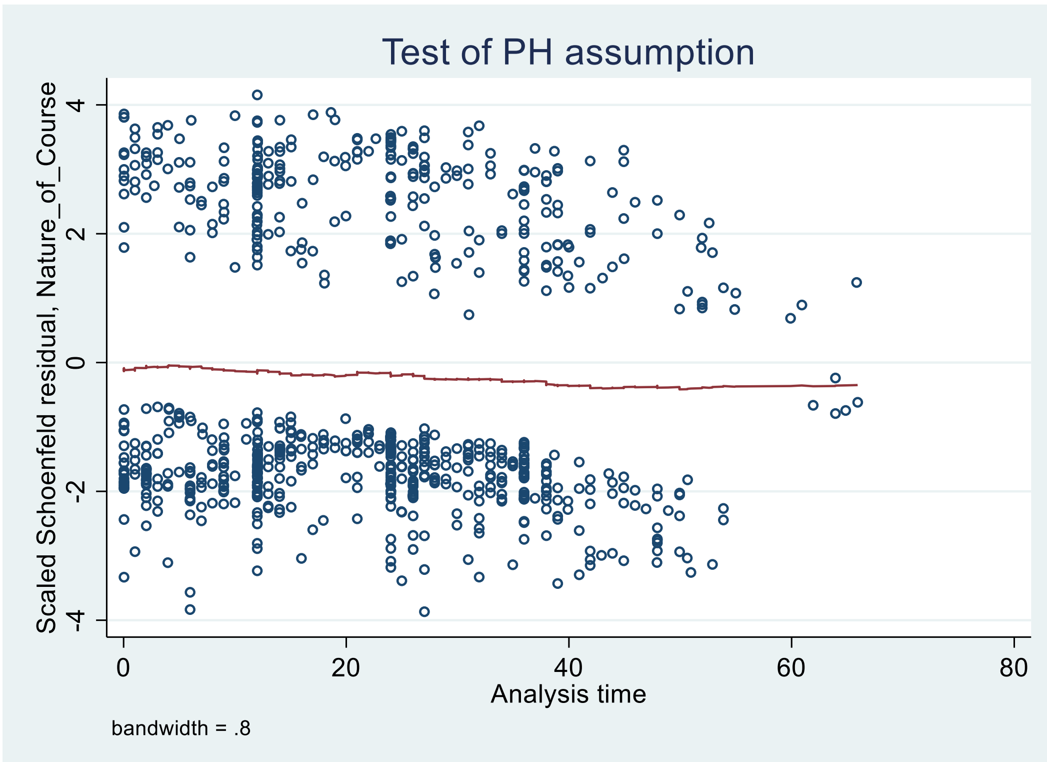

Figure 4:3 Test of PH Assumption

The residuals were randomly scattered around zero without any apparent pattern. This implied that the Cox model was correctly specified with the proportional hazards assumption holding. Additionally, the Cox-Snell residue graph was computed.

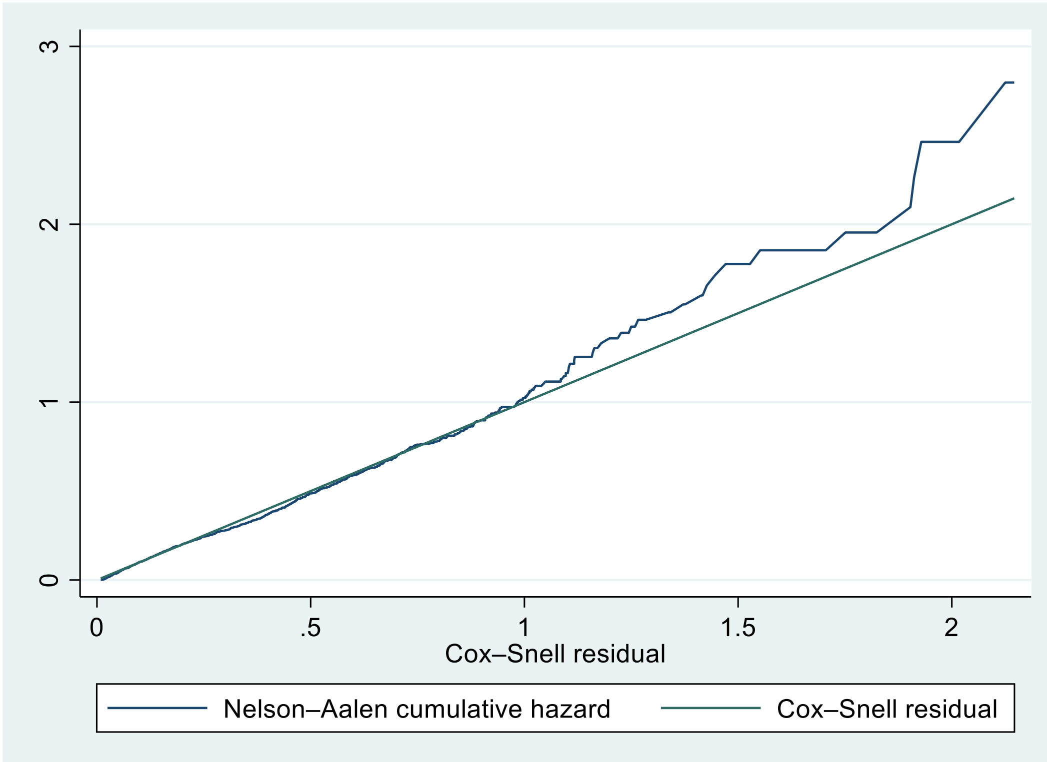

Figure 4:4 Cox Snell Residual Curve

The Cox-Snell residual curve is a diagnostic tool for assessing the fit of a Cox proportional hazards model. The residuals aligned with the reference line, suggesting a good model fit for the data.

The hazard function plot based on survival data was drawn. The smoothed hazard estimate is shown in Figure 4:5

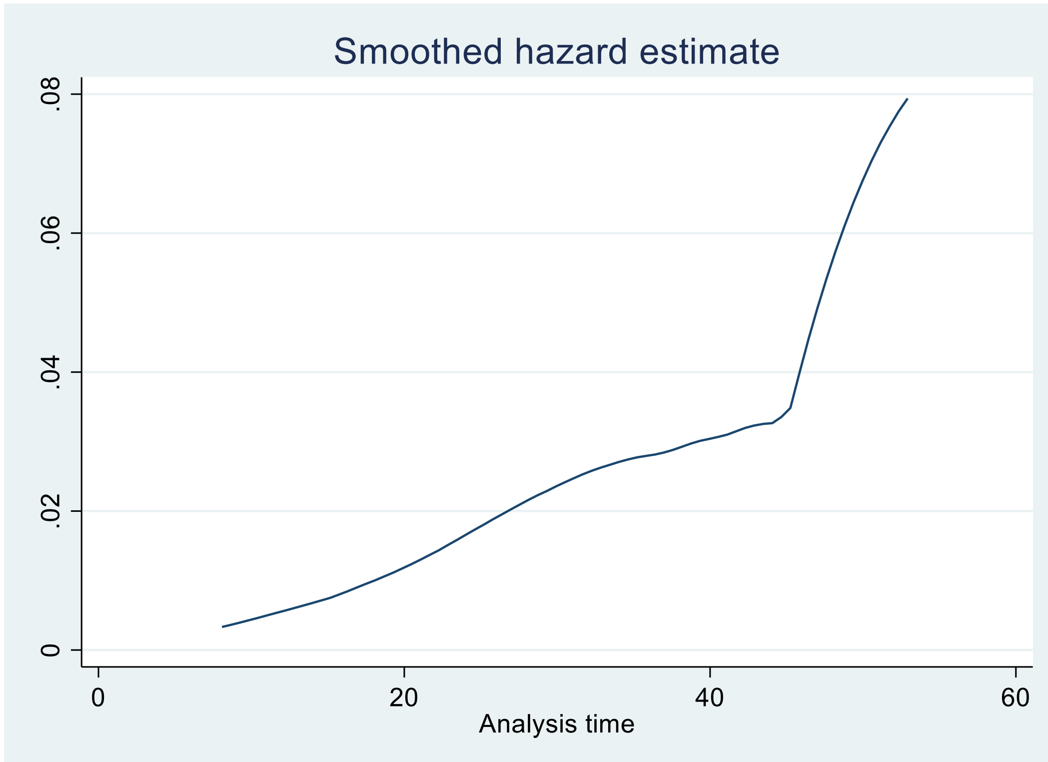

Figure 4.5: Smoothed Hazard Estimate

The hazard curve was non-decreasing over time. It indicated that the employment risk rose as time progressed. It’s noted that beyond 45 months, the hazard curve increase exponentially.

4.4.8 Hypothesis Testing

The null hypothesis for this sub-hypothesis was that the nature of STEM academic programs had statistically significant effect on the unemployment duration of graduates of national polytechnics in Kenya.

(a) H_O1(d): The nature of STEM academic programs has no statistically significant effect on the unemployment duration of graduates of national polytechnics in Kenya.

The study rejected the null hypothesis at $\propto = 0.05$ and concluded that the nature of STEM academic programs had a statistically significant effect on the unemployment duration of graduates of national polytechnics in Kenya.

The result suggests that the nature of STEM academic programs- modular vs non-modular had a significant influence on the unemployment duration of graduates from national polytechnics. This was consistent with Walker (2014), who found that factors beyond program type, such as examination performance, academic qualification, course duration, job search intensity, and age played a significant determining unemployment duration.

In addition, long course duration was found to have a link to quicker job placements suggesting that extended training enhanced employability. Weiss (2014) argued that long course duration offer more thorough skill development, increasing respondents' competitiveness in the job market. These programs often provide more networking opportunities, internships, and job placements, directly contributing to faster employment.

However, some studies challenge this, suggesting that training quality and its relevance to market demands were more important than duration. Mourshed et al. (2014) argue that shorter, targeted courses can sometimes be more effective, offering relevant skills that match employers' needs. Additionally, graduates may still face difficulties if the course curriculum doesn't align with industry trends or if they lack essential soft skills (Saks, 2015). Thus, while longer courses have certain benefits, their effectiveness in enhancing employability depends on content and market relevance.

Active and persistent job search strategy, where early and frequent applications are associated with faster employment are consistent with findings of Caliendo (2015) and McGee(2015). This suggests that putting in substantial effort into job searching significantly boosts employment prospects, while moderate efforts do not show the same impact on securing a job. In addition, Card et al., (2015) suggest that intensive job search efforts, including submitting more applications, are associated with better employment outcomes. In contrast, other research has suggested that factors such as individual motivation and external circumstances might influence the effectiveness of job search strategies, indicating that intensity alone may not always guarantee quicker employment (DellaVigna et al., 2022).

This study further established that controlling for geographical mobility, potentially to urban areas, was associated with a faster employment process. These results agree with Buch et al., (2014) who highlighted the role of geographic mobility in improving access to job opportunities, especially in regions with higher demand for labour. Urban areas typically offer more diverse employment options and networks, which could expedite the job search process. However, De Brauw et al. (2014) suggest a contrasting view, where older graduates tend to find jobs slightly faster, possibly due to their greater work experience or a more mature and strategic approach to job searching. Similarly, D'Amuri and Peri (2015) posit that migration often leads to overqualification and job mismatches, potentially resulting in suboptimal employment outcomes, which contrasts with the belief that migration consistently enhances job prospects.

Failing exam grades were associated with a significantly longer time to employment aligning with Phillips' findings (2017), which emphasize the negative impact of poor academic performance on job prospects. Poor exam results can signal to employers a lack of required skills or preparedness, leading to prolonged job searches. However, contrary findings by Hovdhaugen, (2015) suggest that academic performance may not always be the most critical factor in securing employment. Hovdhaugen’s research points to the possibility that work experience, networking, and personal attributes might play a more decisive role, challenging the notion that exam results are always a determining factor in employment outcomes.

The result suggesting that graduates from 2019 experienced faster job placements likely reflects more favourable economic conditions or better alignment between educational outcomes and the job market during that year. Economic growth or a stronger labor market in 2019 may have led to more available job opportunities, allowing graduates to secure employment more quickly. Additionally, there could have been a closer match between the skills acquired through academic programs and the skills in demand by employers, making these graduates more attractive candidates. Such conditions might have resulted in quicker transitions from education to employment, highlighting the impact of external economic factors and market demand on employment outcomes.

In summary, the hazard ratios revealed that certain factors like course duration, job search efforts, and recent graduation years were positively associated with quicker employment. The nature of the course and failing grades were notably associated with longer times to employment. These findings underscore the importance of educational structure, proactive job searching, and timing in influencing employment outcomes.

Responses from an interview with one of the registrars suggested that;

> "*Modular education programs, which segment learning into smaller, flexible units, significantly influence unemployment duration by enhancing alignment with labour market needs. These programs allow students to acquire targeted skills and credentials quickly, addressing specific industry demands.".* Additionally on examination performance with regard to job placement, they pointed out that *"The significant impact of exam failures on employment risk also aligns with our understanding of how academic performance directly influences job readiness."*

Together, these studies underscore the complex interplay of factors such as job search strategies, migration patterns, and marital status in shaping employment dynamics, offering valuable insights into understanding and improving labour market outcomes.

4.5 The Level of STEM Academic Programs on Labour Market Outcomes

The second objective sought to establish the effect of level of academic programs on labour market outcomes. The study had four outcome variables (labour market outcomes); Earning, employment status, sector of employment and unemployment duration. The data on this was analysed and presented in the following sequence: First, the distribution of the level of STEM academic programs; regression analysis to examine the effect of the level of STEM academic program on earnings; a multinomial regression to assess the relationship between the level of STEM academic program and employment status; a survival analysis using semi paramedic Cox proportional hazards and parametric Weibull method to compute the unemployment duration probability. Control variables included; Gender, A10_Age, SpellDuration, migration_TO, AcadQual, Scapital, CourseAdvance, jsi, year of completion, Examgrade, Marital_Status, Migration_Dummy, ReservationWage2, Applications8wks, and course duration.

4.5.1 Level at the Start of the Course

Figure 4.6 classified respondents based on their educational level at the beginning of their courses, providing insights into the distribution of students across different starting levels.

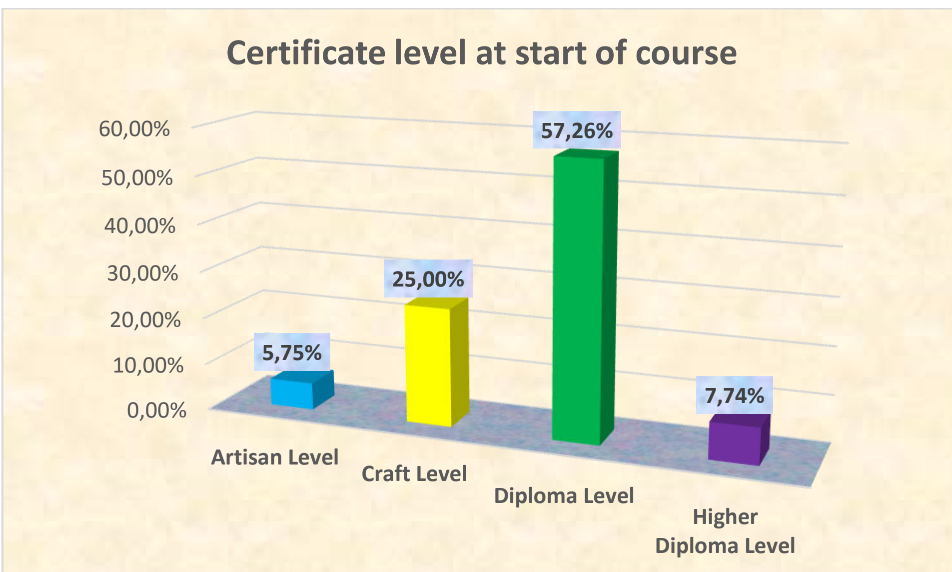

Figure 4.6 Level at Start of Course

A relatively small proportion, 5.75%, began their courses at the "Artisan Certificate Level," suggesting a foundation level of education. A more substantial portion, 25%, started at the "Craft Certificate Level," indicating a mid-level starting point in their educational journey. The majority of respondents, comprising 57.26%, commenced their courses at the "Diploma Certificate level," highlighting the prevalence of diploma programs. A smaller but notable group, 7.74%, began their courses at the "Higher Diploma Certificate Level," signifying a higher level of initial qualification.

Table 4.22 Level of Certificate and Earnings

Variable	**Mean Earnings**	**Std. err.**
Level of Certificate		
Artisan	8705.43	1737.27
Craft	11460.84	1608.10
Diploma	13214.63	775.61
Higher Diploma	8703.70	5721.41
Sector		
Private	36132.39	1666.413
Public	42239.08	2247.065
Hotelling T^2 354.89	Hotelling F	0.000

Note. The Hotelling T^2 value of 354.89 and the associated Hotelling F statistic($p<0.001$) suggest that the level of certification significantly influenced earnings.

Table 4.22 presents the mean earnings and standard errors (Std. err.) for respondents based on their level of certification and the sector they work in. The mean earnings increased with higher levels of certification up to the diploma level. Respondents with a Diploma earned the highest (mean earnings of 13214.63), followed by those with Craft certificates (11460.84), and those with Artisan certificates (8705.43). However, respondents with Higher Diplomas had mean earnings of 8703.70, which are unexpectedly lower than those with Diplomas and similar to those with Artisan certificates. The high standard error for Higher Diploma holders (5721.41) suggested considerable variability in their earnings.

Overall, while higher certification levels generally correlated with higher earnings, the anomaly for Higher Diploma holders suggested a further investigation. Employees in the

Private sector had a mean earning of KSh 36,132.39 with a standard error of KSh 1,666.41, while those in the public sector earned a mean of KSh 42,239.08 with a standard error of KSh 2,247.07. The data shows that earnings are significantly higher in the public sector compared to the Private sector, indicating that, on average, employees in the public sector earn more than those in the private sector with earnings in the public sector exhibiting more variability.

The bivariate test for means of Level of Certificate and Earnings revealed significant differences across the groups. The Hotelling T^2 statistic was 354.89, and the corresponding Hotelling F statistic was also 354.89, both were statistically significant ($p < 0.001$). Given this p-value, the null hypothesis that the means of level of certificate and earnings were the same across all groups was rejected, indicating that different levels of certification were associated with different mean total earnings. This led to a multivariate analysis that employed a multiple linear regression.

4.5.2 Multiple Linear Regression of Level of Certificate on Earnings

Regression analysis of the level of STEM academic Certificate on earnings was performed. This analysis aimed to assess how varying levels of certification influenced income across multiple categories, providing insights into the effect of educational qualifications on earning potential.

The general regression was given by;

$$Y=\beta 0+\beta_1 X_1+\beta_2 X_2+\cdots+\beta_k X_k+\epsilon$$

Where Y = Earnings, β_0 = Intercept/constants, $\beta_1, \beta_{2,}, \beta, \beta_k$ are regression coefficients of respective predictors, and X_1, $X_{2...}, X_k$ are independent variables, ϵ = Error term.

The Predictor variable was the level of academic certificate in categorical form. This were Artisan, craft, diploma and higher diploma levels of certification. The study included several control variables to account for factors that could potentially influence total earnings. These control variables were **Gender**, **Employment Category (EmployCat)**, **Migration Status (migration_TO)**, **Reservation Wage (ReservationWage)**, **Exam Grade (Examgrade)**, and **Marital Status (Marital_Status) and year of completion**. By including these variables, the analysis controlled for the effects of gender, employment status, migration patterns, academic performance, expected wages, and marital status, allowing for a more accurate assessment of the relationship between nature of the course and total earnings.

4.5.2.1 Assumptions of the Regression Model

The study made several key assumptions for the linear regression analysis. These assumptions included: linearity; independence; homoscedasticity; normality; no multicollinearity. The assumptions of homoscedasticity, multicollinearity, normally distributed residuals, correct model specification, appropriate functional form, and the identification of influential observations were examined using the Stata "regcheck" function as proposed by Mehmetoglu (2014).

The Breusch-Pagan test was used to check for homoscedasticity, where a p-value < 0.05 indicated heteroscedasticity (Gujarati, 2012). Variance Inflation Factor (VIF) values were utilized to detect severe multicollinearity, with a VIF above 5.0 indicating a problem (Studenmund, 2013). The Shapiro-Wilk W test was employed to assess the normality of residuals, with a p-value < 0.01 suggesting non-normality, supplemented by residual plots for additional insight. The model specification was tested using the link test, where a significant _hatsq ($p < 0.05$) indicated a specification issue (StataCorp, 2023). Ramsey's RESET test was applied to verify the functional form, with a p-value < 0.05 indicating a problem (Wooldridge, 2019). Cook's distance (D) identified influential observations, where $D > 1$ suggests significant influence (Pardoe, 2008; Pardoe, 2006). The results are as shown in table 4.27

Table 4.23 Regression Diagnostics Test

Regression assumptions	**Test**	**We seek values**
1) Heteroskedasticity problem	Breusch-Pagan hettest	> 0.05
	Chi2(1):1215.64	
	p-value: 0.000	
2) Multicollinearity problem	Variance inflation factor	< 5.00
	Jsi	1.02
	Educsponsor	1.22
	Examgrade	97.37
	Marital_Status	81.63
	Migration_Dummy	43.53
	A15_LevelofCert	1.06
	ReservationWage2	1.05
	Applications8wks	1.1
	EmployCat	1.49
	A15_LevelofCert	1.12
	Gender	1.04
	migration_TO	1.17
	AcadQual	3.13
3) Residuals are not normally	Shapiro-Wilk W normality test	
	t: 14.465	
	p-value: 0.000	> 0.01
4) Specification problem	Linktest	
	t: 11.849	
	p-value: 0.000	> 0.05
5) Functional form problem	Test for appropriate functional	
	F(3,1410):65.773	
	p-value: 0.000	> 0.05
6) No influential observations	Cook's distance	< 1.00
	no distance is above the cutoff	

The diagnostic tests for the multinomial regression model revealed significant issues on several key assumptions. The Breusch-Pagan test indicated a heteroskedasticity problem, as evidenced by a p-value of 0.000, well below the desired threshold of 0.05. This result suggested that the variance of the residuals was not constant, violating the assumption of homoscedasticity. Additionally, the Shapiro-Wilk normality test showed that the residuals were not normally distributed,($p < 0.001$), indicating a deviation from the normality assumption.

Multicollinearity was a major concern in the model, with several variables exhibiting extremely high Variance Inflation Factor (VIF) values. For instance, variables such as A15_LevelofCert, CourseAdvance, and various levels of Examgrade had VIFs far exceeding the acceptable limit of 5. This indicated that these predictors were highly correlated with each other, which could distort the regression coefficients and make the model's estimates unreliable. Other variables however had VIFs below 5, suggesting that multicollinearity was not a problem for these specific predictors. Furthermore, the model faced specification and functional form issues.

The Linktest for model specification suggested misspecification ($p < 0.001$). Despite these issues, the Cook's distance measure showed no influential observations, meaning that no single data point unduly influenced the model.

Due to the violations of these assumptions, robust regression was employed, utilizing the Huber-White sandwich estimator to provide robust standard errors against heteroscedasticity and other forms of misspecification (Fox, 2015). Robust regression was particularly useful when the data contains outliers or influential data points that could unduly affect the results of a standard linear regression model.

4.5.2.2 Regression Analysis of Level of Certificate on Earnings

Table 4.24 shows the regression analysis of Level of Certificate on Earnings

Table 4.24 Multiple Linear Regression Level of Certificate on Earnings

Total_Earnings	Coefficient	std. err.	t	P>t
A15_LevelofCert				
Craft	-1603.26	2914.85	-0.55	0.582
Diploma	-2577.46	3754.27	-0.69	0.492
Higher Diploma	-9072.11	8744.63	-1.04	0.300
From Rural to Urban	5596.49	2920.52	1.92	0.056
From Urban to Rural	5850.14	3633.53	1.61	0.108
From Urban to another Urban	9723.92	3928.98	2.47	0.013
Examgrade(Ref Cat: Credit)				
Distinction	1304.17	3082.63	0.42	0.672
Fail	-4156.72	1374.21	-3.02	0.003
Pass	-2376.56	1224.28	-1.94	0.052
Refer	-3781.27	1712.18	-2.21	0.027
Marital_Status(Ref Cat: Married)				
Not Married	-1597.78	760.75	-2.1	0.036
EmployCat				
In Training	-44922.9	12784.35	-3.51	0.000
Employed in different field of study	-43971.2	12653.84	-3.47	0.001
Self-employed in field of study	-45421.2	12677.59	-3.58	0.000
Unemployed	-42738.2	12557.19	-3.4	0.001
EmployCat#c.A15_LevelofCert				
Employed in my field of study	6264.62	2556.12	2.45	0.014
Gender#c.A15_LevelofCert				
_cons	39004.05	15077.04	2.59	0.010

Note. Ref Cat means the reference category of corresponding categorical variable. The # sign means an interaction term.

The robust regression analysis showed that some variables that had statistically significant influence on earnings while other were not. The level of academic certificate (craft, diploma and higher diploma) was not a significant determinant on earnings ($p>0.05$). Respondents who moved from one urban area to another experienced a significant increase in earnings, ($p = 0.013$). Conversely, those who failed and got Refer in their exams had significantly lower earnings, ($B= -4156.719$, $p = 0.003$ and $B = -3781.269$, p

= 0.027). The findings further suggested that married who were not married had significantly lower earnings, (B =-1597.775, p = 0.036) compared to those who were married. The interaction between employment in one's field of study and certification level showed a positive significant impact on earnings (B = 6264.618, p = 0.014).

Hypothesis testing

(b) H_O2(a): The Level of STEM Academic Programs has no statistically significant effect on the earnings of graduates of national polytechnics in Kenya.

The study did not reject the null hypothesis at $\propto = 0.05$ and concluded that the level of STEM academic certificate programs had no statistically significant effect on the earnings of graduates of national polytechnics in Kenya.

The finding that the level of academic certification (craft, diploma, and higher diploma) is not a significant determinant of earnings challenges the prevailing theory that higher educational qualifications directly lead to higher earnings (Marginson, 2019; Bowen, 2018). This theory, rooted in human capital theory, suggests that respondents with more education typically have access to better job opportunities, higher wages, and greater job security (Kahn, 2018; Mirowsky, 2017). However, the results seem to suggest that in some contexts, particularly within technical and vocational education and training (TVET), other factors—such as work experience, skills, and industry demand—may play a more significant role in determining earnings than formal educational attainment (Vincent & Rajasekhar2023; Wongmonta, 2023).

In many developing economies, the labor market for TVET graduates often emphasizes practical experience over formal qualifications, as industries may prioritize job-specific skills rather than academic credentials (Kebede et al., 2024). This aligns with the findings of Jensen and Kler (2018), who argue that in some sectors, particularly those focused on technical expertise, the level of education may not be as influential as hands-on experience. Additionally, the relationship between education and earnings is often blurred in oversaturated job markets, where graduates, regardless of their level of education, may face underemployment or be forced to accept jobs that do not require the qualifications they possess (Lavrinovicha, 2015; Pascual-Sáez, 2023). Therefore, while the conventional belief holds that higher education should directly correlate with higher earnings, this may not always be true in specific sectors, such as TVET, where practical experience or other factors can hold greater value.

Findings further suggest that marriage contributes to financial stability, as it provides access to additional resources, which in turn positively influences earnings. This aligns with existing research that demonstrates the economic benefits of marriage, such as shared household expenses and dual income opportunities (Shamblen ,2018). Married respondents tend to experience higher levels of economic security, which may improve their earning potential through increased opportunities for career development or better job offers (Zhang, 2014). Moreover, the economic impact of marriage can extend beyond just financial pooling, as social support and psychological benefits may encourage better career outcomes (DeMaris, & Oates, 2022). These findings underline the role of marital status as a factor in shaping one's financial well-being and earnings capacity.

The study also revealed that employment category plays a crucial role in determining earnings, with respondents in training, those employed in different fields, those self-employed in their field, and the unemployed all experiencing higher earnings compared to the unemployed group. This highlights the importance of engagement in any form of work or skill-building, as it increases the likelihood of earning a higher income (Bureau of Labor Statistics, 2020). Self-employment, for instance, can lead to greater financial independence and potentially higher earnings compared to traditional employment (Simoes et al., 2016; Falco & Haywood, 2016). Additionally, respondents in training or those working outside their field of study may gain unique skills or experiences that increase their market value, ultimately resulting in higher wages (Yang, 2018). These findings emphasize that active participation in the labor market, regardless of employment status, is integral to improving one's earnings trajectory.

4.5.3 Level of STEM Academic Programs and Employment Status

The fifth sub hypothesis sought to establish the effect of level of STEM academic program on employment status of graduates on national polytechnics in Kenya. Employment category status included: employed in the field of study, employed in a different field of study, self-employed in the field of study, self-employed in a different field of study, and unemployed. This analysis aimed to reveal how the academic certification levels in STEM influences career paths and employment categorization.

4.5.4 Descriptive Statistics for Employment Status

Table 4.25: Distribution of Level of Certificate and Employment Category

Level of Certificate	Employed different field of study	Employed field of study	In Training	Self-employed different field of study	Self-employed in field of study	Unemployed	Total
Artisan	11	23	1	20	12	62	129
Craft	25	74	8	37	21	147	312
Diploma	97	230	21	140	103	414	1,005
H.Diploma	2	5	2	3	5	10	27
Total	135	332	32	200	141	633	1473
Pearson chi2(15) = 16.9 Pr = 0.319							

Note: Respondents with Diploma qualification had the highest frequency followed by Craft level qualification. Higher diploma qualification had the least frequency. The Pearson chi square value of association between the level of certificate and the employment status was not significant($p>0.05$).

4.5.5 Correlation between the level of STEM academic qualification and employment status.

The results of the Pearson chi values showed the association between the level of academic certificate and employment status was not significant$\chi^2(15, 1473) = 16.9$, $p= 0.319$. This however, did not rule out the possibility that other variables could influence the relationship between the level of academic certificates and employment status. Consequently, a multivariate analysis was performed utilizing a multinomial logistic regression.

4.5.5 Multinomial Logistic Model for Level of Academic Program and Employment Status

A multinomial logistic model was used for predicting the effect of employment status on level of STEM academic programs. The outcome dependent variables were categorical. These were; employed in a different field of study, employed in my field, in training, self-employed in a different field of study, self-employed in the field of study, and unemployed. The model compared each category against a reference category-unemployed, with coefficients representing the log odds of an outcome falling into a particular category versus the reference category(unemployed).

Table 4:26 Multinomial Logistic Regression of Level of Academic Program and Employment Status

Variable	**Employed in a Different Field of Study**		**Employed Field of Study**		**In Training**		**Self Employed in a Different Field of Study**		**Self Employed in Field of Study**	
A15_LevelofCert	RRR	P>z	RRR	P>z	RRR	P>z	RRR	P>z	RRR	P>z
Craft	1.673	0.285	2.930	0.002	12.95	0.027	0.659	0.270	1.009	0.984
Diploma	2.963	0.067	5.684	0.000	1.690	0.008	0.859	0.742	2.186	0.138
Higher Diploma	1.607	0.618	3.063	0.104	1.090	0.001	0.935	0.931	3.084	0.144
Gender										
Male	1.180	0.428	1.462	0.015	2.059	0.108	1.262	0.190	1.613	0.024
A10_Age	1.018	0.619	1.043	0.104	0.976	0.736	1.061	0.046	1.074	0.030
CourseDuration	0.974	0.115	0.975	0.024	0.985	0.577	1.002	0.845	0.981	0.167
SpellDuration	1.138	0.009	1.024	0.413	1.038	0.665	1.041	0.260	1.006	0.849
migration_TO										
From Rural to Rural	1.7028	0.000	0.088	0.002	0.478	0.995	0.478	0.989	0.478	0.530
CourseAdvance										
Advanced by 1 year	1.366	0.427	2.429	0.001	1.863	0.000	1.063	0.851	1.195	0.633
Advanced by 2 years	1.725	0.528	2.945	0.071	1.963	0.001	0.000	0.988	4.288	0.022
jsi										
High	1.607	0.000	1.447	0.038	1.000	1.000	2.580	0.000	1.221	0.394
Educsponsor										
County Government/CDF	11.946	0.095	12.888	0.046	7.348	0.999	4.546	0.343	12.380	0.133
Marital_Status										
Not Married	1.040	0.852	0.772	0.106	1.524	0.001	1.468	0.031	0.946	0.792
Migration_Dummy										
Migrated	0.854	0.535	0.886	0.521	1.146	0.802	0.695	0.090	0.568	0.017
Applications8wks	1.144	0.001	1.098	0.046	1.128	0.746	1.076	0.108	1.096	0.974
Cons	0.306	0.556	0.117	0.172	0.000	0.988	0.000	0.985	0.020	0.067
Base Outcome Category: Unemployed										

Employment in a Different Field of Study Categorical Outcome

The findings suggested that the level of academic certificate was not statistically significant for graduates who were employed in a different field of study (RRR= 1.673, P= 0.285). However, when controlling for job applications, each additional application submitted (Application8WKS) was associated with a 14.9% higher relative risk of finding employment in a different field relative to remaining unemployed (RRR = 1.144, p = 0.001< 0.05). Respondents who migrated (migration_TO) had a 70.28% higher chance of finding employment in a different field compared to those who did not migrate (RRR = 1.7028, p = 0.000, p< 0.05). High job search intensity compared to low job search intensity was associated with a 60.7% higher chance of finding employment in a different field (RRR = 1.607, p <0.001).

Employed in Same Field of Study Categorical Outcome

Findings for graduates employed in the same field of study suggested that the level of academic certificate was statistically significant. Specifically, respondents with craft level of certification were 193% more likely to be employed in same field of study compared to those with artisan certificate (RRR= 2.930, p < 0.001). For those with Diploma level of certificate, they were 468% more likely to be employed in same field of study compared to those with artisan certificate (p =0.002).

Additionally, Males were 46.2% more likely to be employed in the same field of study compared to females (RRR = 0.462, p < 0.05) and course duration had a negative but significant effect on employment in the same category (RRR= 0.975, p < 0.01). Longer course duration decreased the likelihood of being employed in the field of study by 2.5% for each additional increase in months of unemployment.

Training Categorical Outcome

The study findings suggested that the level of academic certificate was statistically significant for graduates who were "In Training". Respondents with diploma level of certificate were 69.7% more likely to be in training compared to being unemployed. Additionally, those who advanced in their course to a higher level were 96.3% more likely to be in training compared to being unemployed ($RRR = 1.96.3$, $p < 0.001$). Marital status also played a role, with unmarried respondents being 52.4% more likely to be in training compared to those who were unemployed ($RRR = 1.524$, $p < 0.05$).

Self-Employed in a Different field of Study Categorical Outcome

Study findings suggested that the level of academic certificate was not statistically significant for graduates who were self-employed in a different field of study($P>0.005$). However, when controlling for age, each additional year in age increased the likelihood of being self-employed in a different field by 6.1% compared to being unemployed ($RRR = 1.061$, $p < 0.05$). Further, males were 26.2% more likely to be self-employed in a different field compared to females ($RRR=1.262$, $p < 0.05$) and having a high job search intensity (JSI) increased the relative risk of being in self-employed in a different field of study by 157.9% ($p < 0.05$) compared to those unemployed.

Self-Employed in the Same Field of Study Categorical Outcome

The results of the study suggested that the level of academic certificate was not statistically significant on graduates who were self-employed in same field of study($P>0.005$). However, when controlling age, each additional year in age increased the likelihood of being self-employed in the same field of study by 7.4% (RRR= 1.074, $p < 0.05$) and males were 61.3% more likely to be self-employed in same field of study compared to females (RRR = 1.613, $p < 0.01$). Migration patterns also influenced this category, as respondents who did not move were 43.2% less likely to be self-employed in the same field of study compared to those who did (RRR = 0.567, $p < 0.05$).

4.5.3.2 Diagnostic Tests for Multinomial Logistic Regression

A post analysis diagnostic test of the multinomial logistic regression was performed. The assessments included checking the Independence of Irrelevant Alternatives (IIA), goodness-of-fit, multicollinearity, outliers, and model specification. These tests were crucial in identifying and addressing potential issues, which helped improve the robustness of the analysis. Each diagnostic test offered unique insights into the model's performance and reliability, and conducting these tests comprehensively was essential for achieving accurate and reliable results. Table 4.29 gives summary diagnostic tests.

Table 4.27 Diagnostic Test for Multinomial Logistic Model

	Coefficients			
	M1	**M2**	**Difference**	**Std.err.**
Independent Irrelevant Alternative test				
Nature of Course	-0.0235834	0.088411	-0.1119943	0.091
Test of H0: Difference in coefficients not systematic				
chi2(1) = (b-B)'[(V_b-V_B)^(-1)](b-B)				
= 2.63				
Prob > chi2 = 0.3281				
Goodness-of-fit test				
Dependent variable: EmployCat				
chi-squared statistic = 29.331				
degrees of freedom = 40				
Prob > chi-squared = 0.402				

The Hausman test compared the coefficients from models M1 and M2 to assess if they differed systematically for the composite outcome variable Employment Category in measuring the independent irrelevant alternative. The test indicated that the difference in coefficients for the variable Nature of Course was not statistically significant, ($\chi^2(6, 1463)$ = 2.63, p= 0.3182 suggesting that there was no systematic difference between the coefficients of the models.

This suggested that the choice of the reference category did not negatively impact on the outcome. The goodness-of-fit test for the multinomial logistic regression model, assessed the model's fit to the data. The chi-squared statistic was statistically not significant ($\chi^2(6, 1463)$ = 29.331, p= 0.402 suggesting that the model adequately fit the data.

Hypothesis testing

(c) $H_O2(b)$: The Level of STEM Academic Programs has no statistically significant effect on the employment status of graduates of national polytechnics in Kenya.

The study rejected the null hypothesis at $\propto = 0.05$ and concluded that the level of STEM academic certificate programs had a statistically significant effect on the employment status of graduates of national polytechnics in Kenya.

The results suggest that the level of academic certificate does not significantly affect the employment outcomes of graduates employed in a field different from their area of study, aligning with findings from Jepsen et al. (2014) and Dadgar & Trimble (2015), who also found minimal influence of academic certification on such employment scenarios. However, when controlling for factors like geographical mobility, job search intensity, and the number of job applications, the results remained positive, indicating that these factors play a more substantial role in securing employment. This suggests that while the level of academic certification may not directly impact employment in an unrelated field, factors such as active job search strategies and mobility are crucial in improving job placement outcomes.

The findings showed that the level of academic certification significantly impacted employment in the same field. This supports Kotey, S. (2024) and Mashongoane, T. S. (2015), who argue that higher certifications increase employment chances within the same field. Additionally, there were gender disparities in employment in same field of study for both male and female graduates aligning with Betz & O'Connell's findings (1989). The results also suggested that longer course durations reduced the likelihood of field-related employment. Williams (2023) and Fletcher et al. (2017) suggest that extended training might delay entry into the job market or result in less aligned skills, decreasing the chances of staying in the same field.

In addition, results suggest that the level of academic certificate does not significantly impact the likelihood of graduates being self-employed in a different field of study, consistent with Yunus (2018), who found no statistical significance between certification level and self-employment in an unrelated field. However, the findings reveal that age plays a more important role, with each additional year increasing the likelihood of self-employment in a different field by 6.1%, compared to being unemployed. This aligns with Zając (2018), who suggests that older respondents may have more experience, maturity, and perhaps a stronger entrepreneurial mindset, all of which could make them more likely to pursue self-employment, even in fields unrelated to their formal education. In addition, Yunus (2018), found similar findings that for self-employed in the same field of study, the level of academic certificate was not statistically significant.

An Interview schedule with one of the the registrars elicited the following response:

"*Training programs are designed with a strong focus on equipping learners with skills that are highly adaptable and in demand within the industry. We believe that the true value of our education lies not just in the knowledge imparted but in the practical skills* *our graduates acquire. Ideally, these skills should make our graduates stand out in the job market and attract potential employers without the need for prolonged job searches. For those who may not immediately find employment, the versatility of these skills ensures they can be applied across various fields, enhancing their employability in diverse sectors. This approach aligns with the current needs of the Kenyan job market and helps bridge the gap between education and employment."*

4.5.6 The Level of STEM academic Program on Sector Employed

The sixth sub-hypothesis sought to establish the effect of level of STEM academic certificate program on the sector of employment of graduates on national polytechnics in Kenya. The employment sectors were; private and public. This analysis aimed at revealing the relationship between the academic certification levels in STEM on sectors of employment.

Table 4.28: Distribution of Respondents by Level of Certificate and Sector Employed

Level of Certificate	Private	Public	Total
Artisan	18(4%)	16(3%)	34(@21%)
Craft	65(13%)	35(7%)	100(21%)
Diploma	164(34%)	165(#$%)	329(68%)
Higher Diploma	14(#%)	10(2%)	24(5%)
Total	261(54%)	225(46%)	487(100%)
Pearson chi2(3) = 10.5569 Pr = 0.014			

The table presents the distribution of respondents with different levels of certificates across private and public sectors. A higher percentage of respondents with Diploma certification were employed in both the Private (34%) and Public (34%) sectors, making up 68% of the total sample. Craft certificate holders accounted for 21% of the total, with 13% in the private sector and 7% in the public sector. Artisan certificate holders were the smallest group, making up 21% of the total, with 4% in the private sector and 3% in the public sector. Finally, those with a Higher Diploma accounted for only 5% of the total, with 3% in the private sector and 2% in the public sector. This indicates that the Diploma level was the most prevalent certification across both sectors, while Higher Diploma holders are underrepresented in comparison.

The Pearson chi-square test results indicated that there was a statistically significant relationship between the level of certificate and the sector of employment (private vs. public) $\chi^2(15, N= 487) = 10.55$, $p= 0.014$). This suggested that the distribution of certificate levels across the private and public sectors was not random, and the level of certification did have a significant impact on whether respondents are employed in the private or public sector. The study did a further analysis utilising a binary logistic model.

Table 4:29 Binary Logistic Regression of Level of Academic Certificate and Sector of Employment

Sector Privatec	**RRR**	**St.Err.**	**t-value**	**p-value**	**[95% Conf**	**Interval]**
A15_LevelofCert	1.16	0.43	0.39	0.694	.561	2.489
Gender	1.40	0.30	1.56	0.120	.451	1.068
Migration_1	0.95	0.23	-0.21	0.835	.617	1.586
migration_TO	1.00	0.13	-0.02	0.982	.752	1.282
Marital_Status	1.70	0.38	2.38	0.017	.376	.906
A10_Age	1.07	0.04	1.97	0.048	1.001	1.151
Educsponsor	1.09	0.14	0.69	0.492	.862	1.42
Examgrade	0.79	0.06	-3.18	0.001	.671	.906
Jsi	0.91	0.09	-0.91	0.362	.75	1.108
Socialcapital	1.10	0.19	0.55	0.584	.794	1.57
Applicationlas8wks	0.98	0.04	-0.43	0.669	.901	1.062
CourseAdvance	1.41	0.48	1.03	0.304	.763	2.933
AcadQual	0.79	0.19	-1.02	0.307	.491	1.261
Constant	0.12	0.21	-1.22	0.222	.016	21.487
Mean dependent var		1.530	SD dependent var			0.500
Pseudo r-squared		0.070	Number of obs			438
Chi-square		42.385	Prob > chi2			0.000
Akaike crit. (AIC)		591.267	Bayesian crit. (BIC)			648.418
Base outcome: Public Sector						

Note:

The results from the binary logistic regression analysis suggested that Marital Status and Age were significant variables for predicting employment in the private sector($p< 0.05$). Specifically, respondents who were married were 70% more likely to be employed in the private sector compared to the base category (public sector) (RRR= 1.70, p=0.017). Similarly, each additional year of age increased the likelihood of being employed in the private sector by 7.25% (RRR= 1.07, p = 0.048). These findings highlight the influence of personal life circumstances and age on the likelihood of employment in the private sector. Additionally, Exam Grade was also statistically significant (RRR= 0.79, $p< 0.05$), indicating that higher exam grades decreased the likelihood of being employed in the private sector by about 21.4%. The result suggests that respondents with higher academic performance might be more inclined toward other sectors, such as public sector jobs, or they may have better access to positions that require more specific qualifications.

On the other hand, variables such as Level of Certificate, Gender and Migration did not show statistically significant effects on the likelihood of being employed in the private sector (p-values > 0.05) when compared to the public sector. The overall model was statistically significant, suggesting that the model well explained the variation in sector employment(LR chi2(13)= 40.50, $p< 0.001$.

This section gives an analysis of the effect of the level of STEM academic certificate on the sector employed. The outcome variable- sector employed was binary- employment in public or private sector. A binary logistic model was utilised. To ensure the robustness of the binary logistic regression model, several diagnostic tests were performed. The

Hosmer-Lemeshow test (estat gof) assessed the model fit by comparing observed and expected event (Hosmer & Lemeshow, 2000). Cook's distance (predict cooksd) helped detect influential observations that might have disproportionately affected the model (Cook & Weisberg, 1982). Additionally, the linktest command evaluated whether the model appropriately captured the linear relationship between predictors and the logit (Pregibon, 1980). These diagnostics collectively ensured that the logistic regression analysis was valid and reliable. The table 4.30 shows the results.

4.5.4.1 Diagnostic Tests for the Logistic Regression

Diagnostic tests for the binary logistic regression were performed.

Table 4.30 Diagnostic Tests Logistic Regression

Logistic regression				**Number of obs**	**460**
				LR chi2(2)	43.21
				Prob > chi2	0
Log likelihood = -296.38773				Pseudo R2	0.0679
Goodness-of-fit test after logistic model					
Hosmer–Lemeshow chi2(8) =	5.59				
Prob > chi2 =	0.6928				
Sensitivity	Pr(+ D)	72.40%			
Specificity	Pr(-~D)	49.77%			
Correctly classified		61.88%			
Linktest results					
SectorEmpl Coefficient	Std. err.	z	P>z	[95% conf.	interval]
_hat	1.02187	0.174	5.87	0.000	0.68083
_hatsq	-0.1032	0.20237	-0.51	0.610	-0.4998
_cons	0.03386	0.11954	0.28	0.777	-0.2004
Pearson Chi-Square Test					
Pearson chi2(444) =	341.81				
Prob > chi2 =	0.1618				

The diagnostic tests for the logistic regression model predicting SectorEmpl indicated a generally well-fitting model. The Hosmer-Lemeshow test suggested that the model's predicted probabilities aligned well with the observed outcomes, ($\chi^2(1, 807) = 5.59$, p= 0.6928. The classification table showed a sensitivity of 72.40% and a specificity of 49.77%, with an overall correct classification rate of 61.88%, reflecting moderate predictive performance. The linktest results, where the linear term _hat is significant but the squared term _hatsq is not, suggested the model was appropriately specified without evidence of model misfit. Additionally, the Pearson chi-square test further supported the model fit with no significant discrepancies between observed and expected values($\chi^2(1, 807) = 341.81$, p= 0.1618. Overall, these diagnostics collectively indicated a reasonably well-fitting logistic regression model

Hypothesis Testing

The null hypothesis for this sub hypothesis was;

$H_0$2(c): The level of academic certificate programs has no statistically significant effect on Sector of employment of graduates of national polytechnics in Kenya. The study did not reject the null hypothesis at $\propto = 0.05$ and concluded that level of academic certificate programs had no statistically significant effect on Sector of employment of graduates of national polytechnics in Kenya.

The results suggested that respondents who were married were more likely to be employed in the private sector compared to those in the public sector, supporting findings from Laird (2017) and Bullock et al. (2018), who also observed that marital status can influence employment outcomes, particularly in the private sector. This suggested that marital status may be associated with greater stability or economic responsibility, which could make respondents more attractive to private employers. Additionally, the results highlight the role of **age** in employment decisions, with younger respondents being more likely to be employed in the private sector. This aligns with Ertas (2016), who noted that age brings a flexible and technology sensitive experience, which are valued traits by private sector employers, potentially enhancing job prospects and stability.

Higher exam grades were statistically significant in decreasing the likelihood of being employed in the private sector. This finding contrasts with previous research by Hansen et al. (2024) and Kittelsen & Helland (2017), who found that higher academic performance is typically associated with better employment outcomes, particularly in the private sector. The results imply that respondents with higher exam grades might be more inclined to pursue opportunities outside the private sector, possibly in academia or public sector roles, or that employers in the private sector may prioritize practical experience over academic performance. However, this contrasts with the findings of Araki et al. (2016), who argue that graduates from elite schools, who typically perform better academically, are often promoted quickly within companies due to their perceived higher job performance. This contradiction suggests that the relationship between exam grades and employment outcomes could be influenced by industry type, job role, or other factors beyond academic performance.

The results further showed that the level of certificate, gender, and migration did not show statistically significant effects on the likelihood of being employed in the private sector.

This suggested that despite the varying educational levels, demographic characteristics, and mobility patterns, did not significantly influence the probability of securing private sector employment. This aligned with the findings of Do Monte (2017), who noted that, in certain contexts, education and migration may not always have a direct impact on employment outcomes in the private sector. However, the findings by Leyaro & Joseph (2019) provided an alternative perspective, suggesting that there are low returns to investment in TVET. According to their research, TVET qualifications may not always lead to better job opportunities in the private sector, reflecting a mismatch between the skills taught in vocational programs and the skills demanded by private employers.

The FGDs with office of career officers revealed that:

"Respondents with better academic performance are more likely to be employed in the private sector, as it tends to value high academic achievements more highly, offering better opportunities and incentives for those with superior academic records."

4.5.5 Level of STEM Academic Program and Unemployment Spell

The final analysis of this second objective was to analyse the level of academic certificate on unemployment duration of graduates of national polytechnics in Kenya. The study utilised a survival analysis model. The analysis used semi-parametric test, and parametric tests to model these survival functions. Results of the analysis were compared and conclusion made. The predictor variable ware; the level of academic certificate- artisan, craft, diploma, and higher diploma. Other control variables included; number of job application (Applications8weeks), geographical mobility (MigrateTo), Gender, Age, job search intensity(JSI), Reservation wage, academic qualification(AcadQual). Exam Grade, and year of completion.

4.5.5.1 Description of Survival Data

The study sought to analyse descriptive statistics that included incidence rate, time at risk and median survival time of the data set.

Table 4:31 Median Survival Probability

Nature of course	Time at risk	Incidence rate	Number of Subjects	------ Survival time…. 25%	50%	75%
Artisan	5,936.10	0.01095	128	31.01	60.92	
Craft	12,226.20	0.012596	309	26	50.62	65.83
Diploma	26,625.15	0.020995	995	14.03	31.93	52.59
Higher Diploma	1,055.77	0.013261	26	18.95	47.93	

Table 4.31 provided insights into the survival analysis for different education certificate levels in months to employment. For each certification type—Artisan, Craft, Diploma, and Higher Diploma—the median survival time indicated the time by which 50% of the respondents were expected to have secured employment. Specifically, respondents with an Artisan Certificate had a median time to employment of approximately 60.92 months (95%CI: 57.874- 63.966), meaning that half of these respondents found employment within this period. For those with a Craft Certificate, the median time to employment was 50.62 months (95%CI: 48.089-53.151). Those with a Diploma Certificate have a shorter median time to employment of 31.93 months (95%CI: 30.333-33.526), suggesting they found jobs more quickly than respondents with other certificates. Respondents with a Higher Diploma Certificate had a median time to employment of 47.93 months (95%CI: 45.5335-50.3265)

Overall, the total median time to employment across all certificate levels was 37.97 months. This indicated that, on average, respondents from all education levels secured employment within this period. The differences in median times to employment reflected the varying likelihood of finding a job based on the type of certification. Artisan Certificate holders had the longest median time to employment, while Diploma Certificate holders had the shortest.

4.5.5.2 Association between level of Academic Certificate and Survival Time.

The study sought to establish whether there was any association between the level of academic certificate and the survival time.

Table 4.32 Log-Rank Test for Level of Certificate

Level of Certificate	**Observed Event**	**Expected Event**
Artisan	65.000	106.95
Craft	154.000	211.36
Diploma	559.000	455.48
Higher Diploma	14.000	18.21
Total	792.000	792.00
	chi2(3)=	63.21
	Pr>chi2=	0.000

The log-rank test revealed a significant difference in employment rates for the four levels of certification $\chi2(3, N=792) = 63.21$, $p < 0.001$ suggesting that the discrepancies between the observed and expected events were statistically significant. Specifically, the artisan, craft, diploma, and higher diploma levels showed variations in the number of observed versus expected events, with the diploma level having the most notable deviation. This indicates that the certificate level had a significant impact on the employment event rates. A multivariate analysis was performed to help if there existed more complex patterns in this relation. A semi parametric analysis utilising the cox proportional hazard was performed.

4.5.5.3 Cox Proportional Hazard Function for Graduates' Level of Certificate & the Survival Time.

A Cox proportional hazard function examined the relationship between the level of academic certificate program and survival time. The function assumed that the effect of the predictor variables on the hazard rate was multiplicative and remained constant over time. This method often preferred over the Kaplan-Meier estimator handles multiple covariates simultaneously, allowing for a more comprehensive understanding of the factors influencing survival. The proportional-hazards assumption test for a Cox proportional hazards model evaluated whether the covariates in the model had hazard ratios that remained constant over time. Table 4.33 shows the results of the proportionality assumption test.

Table 4:33 Proportionality Assumption Test

Predictor Variable	rho	chi2	Df	Prob>chi2
A15_Level of Cert.			1	
Craft	0.002	0.00	1	0.966
Diploma	0.001	0.00	1	0.968
Higher Diploma	0.006	0.03	1	0.861
Gender			1	
Gender (Male)	0.014	0.14	1	0.704
Migrati Dummy			1	
Migrated(1)	0.036	1.02	1	0.312
CourseDuration	0.013	0.13	1	0.714
A10_Age	0.018	0.25	1	0.618
Examgrade			1	
Distinction	0.021	0.36	1	0.551
Fail	-0.029	0.69	1	0.408
Pass	-0.058	2.6	1	0.107
Refer	-0.036	1	1	0.317
Jsi			1	
Medium jsi	-0.022	0.39	1	0.530
High jsi	0.094	7.15	1	0.008
Reservationwage2	-0.005	0.02	1	0.885
CourseAdvance			1	
CourseAdvance(1 Grade)	0.011	0.1	1	0.752
CourseAdvance(2 Grades)	0.032	0.86	1	0.353
Application8weeks	0.046	1.68	1	0.195
Application4weeks	0.020	0.35	1	0.553
Artisan			1	
Craft	0.020	0.33	1	0.566
Degree	-0.010	0.08	1	0.784
Diploma	0.008	0.06	1	0.813
Higher Diploma	0.001	0.00	1	0.984
Global test		37.91	22	0.0187

Each row corresponded to a specific covariate, showing the correlation (rho) between the scaled Schoenfeld residuals and time, the chi-squared statistic (chi2) for testing the assumption, the degrees of freedom (df), and the p-value (Prob>chi2). A rho value close to zero suggested a weaker correlation, implying that the proportional-hazards assumption might hold. Most covariates, such as A15_Level, Gender, Migration, Examgrade, CourseDuration, Age, Reservation, CourseAge, Application, and AcademicQualification, had p-values greater than 0.05, indicating no significant violation of the proportional-hazards assumption.

However, the covariate high JSI was identified as a source of the violation, $\chi 2(22, N=792) =7.17$, p= 0. 0.008w, suggesting a significant violation of the proportional hazards' assumption for the covariate JSI. In addition, the global test, which evaluated the proportional hazards assumption across all covariates collectively showed a significant violation. $\chi 2(22, N=792) = 37.91$, p= 0.0187. This suggested that the model, as a whole, did not meet the proportional hazards assumption, indicating the need for further adjustments or consideration of alternative modelling approach. To address this problem, the study stratified the non-proportional predictor (JSI) (Kleinbaum & Klein, 1996). The results are shown in table 4:37

Table 4:34 Test of Proportional-Hazards Assumption

Variable	rho	chi2	Df	Prob>chi2
Artisan			1	
Craft	0.001	0	1	0.971
Diploma	0.002	0	1	0.947
Higher Diploma	0.007	0.04	1	0.833
Gender	0.014	0.14	1	0.706
Migration	0.032	0.83	1	0.362
CourseDuration	-0.003	0.01	1	0.939
A10_Age	0.022	0.36	1	0.549
Examgrade: Credit	0.027	0.56	1	0.456
Examgrade: Fail	-0.023	0.41	1	0.520
Examgrade: Pass	-0.054	2.26	1	0.133
Examgrade: Refer	-0.037	1.08	1	0.299
JSI			1	
Medium jsi			1	
High jsi			1	
Reservationwage2	-0.012	0.11	1	0.741
CourseAdvance			1	
CourseAdvance by 1grade year	0.012	0.11	1	0.740
CourseAdvance by 2 grade years	0.034	0.96	1	0.326
Application8weeks	0.048	1.84	1	0.175
Application4weeks	0.021	0.39	1	0.531
AcadQual	.	.	1	.
Craft	0.012	0.12	1	0.726
Degree	-0.013	0.14	1	0.712
Diploma	0.004	0.01	1	0.916
Higher Diploma	-0.003	0.01	1	0.934
Global test		29.3	20	0.082

The test of proportional-hazards assumption evaluated showed that the assumption of proportionality had been met after stratification of the covariate jsi. All the covariates in the Cox proportional hazards model maintained constant hazard ratios over time. Additionally, the global test evaluated the proportional hazard assumption for all covariates combined. The results indicated that the proportional hazards assumption was held. $\chi2(20, N=792) = 27.33$, $p= 0.082$. Both individual covariate tests and the global test suggested that the model met the proportional hazards assumption. These results validated the model's use in this analysis.

Table 4.35 Cox Regression Model with Interaction

Level of Certificate	Haz.ratio	Std.err	Z	P>|z|
Craft	0.755	0.1370	-1.550	0.121
Diploma	0.878	0.2063	-0.550	0.579
Higher Diploma	1.043	0.4079	0.110	0.915
Gender				
Male	0.355	0.1509	-2.440	0.015
Migration_Dummy				
Migrated	1.230	0.0966	2.640	0.008
CourseDuration	1.037	0.0060	6.220	0.000
A10_Age	1.023	0.0123	1.920	0.054
Examgrade				
Refer	0.473	3.6213	2.570	0.010
Jsi				
High jsi	1.286	0.1067	3.030	0.002
Applications8wks	0.984	0.0211	-0.750	0.453
Applications4wks	0.954	0.0191	-2.360	0.018
Examgrade#c.Gender				
Credit	3.092	1.2828	2.720	0.007
Fail	3.023	1.3042	2.560	0.010
Pass	3.499	1.4426	3.040	0.002
Refer	1.000	(omitted)		

In the Cox regression analysis using the Breslow method for ties, Gender was a significant predictor of finding employment. Males had a hazard ratio of 0.355 (p=0.015), which indicated that males had a 64.5% lower chance of finding employment compared to females. The Migration_Dummy variable was also significant, with a hazard ratio of 1.230 (p=0.008). This indicated that respondents who migrated had a 23% higher chance of finding employment compared to those who did not. Further, Course Duration had a hazard ratio of 1.037 (p<0.001) and was statistically significant. This suggested that for each additional unit of course duration, the chance of finding employment increased by approximately 3.6%.

The interaction between Exam Grade and gender showed various significant effects on employment outcomes. For instance, respondents with a "Credit" grade had a hazard ratio of 3.092 (p=0.007), which meant that these respondents had a 209.2% higher chance of finding employment compared to the reference category (Refer).

Other significant interactions within the Exam Grade variable included respondents who "Failed" (hazard ratio of 3.023, p=0.010) and those who "Passed" (hazard ratio of 3.499, p=0.002). Respondents who failed had a 53% lower chance of finding employment compared to those who got a Refer. Those who passed had a 249.9% higher chance of finding employment compared to those who got a Refer. These results indicated that exam grades significantly influenced employment outcomes, with those who passed having notably higher chances of finding employment, especially when interacting with gender.

4.5.5.4 Model Estimation Using Cox Regression

Model estimation using Cox regression coefficients involved evaluating the impact of various predictors on the hazard or risk of a finding employment over time. By estimating these coefficients, the relative risk associated with different variables was determined and to understand their influence on survival time. Table 4.36 gives the output.

Table 4:36 Model Estimation Using the Cox Regression Coefficients

Variable	RRR	Std. err.	z	P>z
Level of Academic Cert.				
Craft	0.72	0.13	-1.79	0.074
Diploma	0.82	0.19	-0.88	0.381
Higher Diploma	0.80	0.32	-0.56	0.577
Gender				
Female	2.58	1.01	2.4	0.016
Migration_Dummy				
Migrated	0.81	0.06	-2.64	0.008
CourseDuration	1.03	0.01	6.71	0.000
A10_Age	1.02	0.01	1.98	0.048
Examgrade				
Distinction	1.12	0.28	0.47	0.642
Fail	0.85	0.13	-1.06	0.287
Pass	1.02	0.10	0.16	0.872
Refer	0.58	0.17	-1.89	0.059
JSI				
Medium JSI	1.04	0.10	0.39	0.696
High JSI	1.30	0.11	3.14	0.002
Job Applications	0.95	0.02	-2.34	0.019
AcadQual				
Craft	1.96	0.79	1.67	0.095
Degree	3.17	1.57	2.33	0.020
Diploma	2.36	1.02	2	0.045
H. Diploma	2.37	1.16	1.76	0.078
Examgrade#c.Gender				
Credit	0.33	0.14	-2.69	0.007
Distinction	0.45	0.24	-1.49	0.135
Fail	0.34	0.15	-2.5	0.012
Pass	0.30	0.12	-2.94	0.003
Refer 1 (omitted)				

Note. The reference category for level of academic certificate program is Artisan, for gender is Male, for JSI is Low JSI, for AcadQual is artisan.

This Cox regression analysis examined various factors influencing the time to employment, using the Breslow method for handling ties. The table provided coefficients, standard errors, z-values, p-values, and 95% confidence intervals for each variable. The overall model was significant (LR chi2(26) = 157.08, $p < 0.001$), indicating that the included variables collectively contributed to explaining the variations in the time to employment.

The Cox regression model investigated the determinants influencing the time to employment for respondents transitioning from unemployment to employment, where the "failure" event denotes the shift from an unemployed to an employed state. Results showed that the level of academic certificate program was statistically not significant in determining the failure event ($p > 0.05$). Further, females were found to be 2.58 times more likely to find employment compared to males (hazard ratio = 2.58, $p = 0.017$). This suggests that females, on average, experience a more rapid transition from unemployment to employment, potentially reflecting greater access to employment opportunities or more effective integration into the labor market.

Geographical mobility (Migration To) significantly impacted the time to employment. There was a slower transition to employment for migrants compared to non-migrants (HR= 0.81, $p = 0.008$). This slower employment transition could be attributed to various factors, such as difficulties related to credential recognition, unfamiliarity with the local job market, or challenges in adapting to a new environment. These findings underscore the potential barriers faced by migrants in securing employment in a new country or region.

The analysis further suggested that course duration was a positive predictor of speed to employment. For every additional year of study, the likelihood of finding employment increased by 3% (hazard ratio = 1.03, $p < 0.0001$). In contrast, age was also a significant factor, with older respondents being more likely to find employment (HR= 1.02, Ip = 0.045 indicating that for each additional year of age, the likelihood of employment increased by 2.4% ($p = 0.045$).

Academic qualifications emerged as a key determinant of speed to employment, with respondents holding a degree being 3.09 times more likely to transition to employment compared to those with lower qualifications (HR = 3.09, $p = 0.023$). Furthermore, respondents with a diploma showed a marginally higher likelihood of finding employment (hazard ratio = 2.32, $p = 0.051$). Job search intensity was also a significant factor, with those engaged in higher intensity job searches being more likely to transition to employment quickly (HR = 1.30, $p = 0.002$).

4.5.5.5 Estimation of the Survival Functions

Each covariate pattern had a different survival function. The default survival function for the covariate pattern was set at each predictor equal to zero. The study modelled survival functions for different settings. The following estimates were established given the predictor variables for subjects at various level of certificates and other covariates.

The Cox proportional hazards model investigated the relationship of predictors and the time-to-event(employment) through the hazard function. It assumed that the predictors had a multiplicative effect on the hazard and that this effect was constant over time.

The general hazard function was given by:

$$h(t\backslash x)= h0(t)e\beta_1 X_1+ \dots \beta_n X_n) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \text{(1)}$$

The predictor variables were; i.A15_LevelofCert i.Gender i.Migration_Dummy, A10_Age, CourseDuration, i.Examgrade, i.jsi, i.CourseAdvance, Applications8wks, A24Whatisthenumberofjoba and i.AcadQual.

The baseline survival function for the covariate pattern where all predictors were set to zero was estimated. The resulting baseline survival function((surv0) was;

$$\text{Surve } (0)= h(t\backslash x)= h0(t)e0= h0(t) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \text{(2)}$$

In order to estimate the survival functions, a hypothetical case is put forward.

Assume a graduate had a craft certificate level (Level =2), Migrated (Migration Dummy=1), was male (Male=2), 30 years old, had a course duration of 2 years, had high job search intensity, and the exam grade was a Refer ((Exam Grade= 4), and made 10 applications in 4 weeks.

The survival function would be;

Surv(01) = h0(t)exp (-0.336Level of Cert-1.529Gender +0.214MigrationDummy + 0.023Age- 0.749ExamGrade + 0.254jsi- 0.049Applications8wks + 32.16AcadQual… **(3)**

A female student with the same characteristics would yield the following survival function:

$$Surv(02)\ exp(h0(t)exp\ (-0.336Level\ of\ Cert-0.214MigrationDummy+0.023Age-0.749ExamGrade+0.254jsi-0.049Applications8wks+32.16AcadQual \quad (4)$$

The resulting survival function estimated is shown in figure 4.6

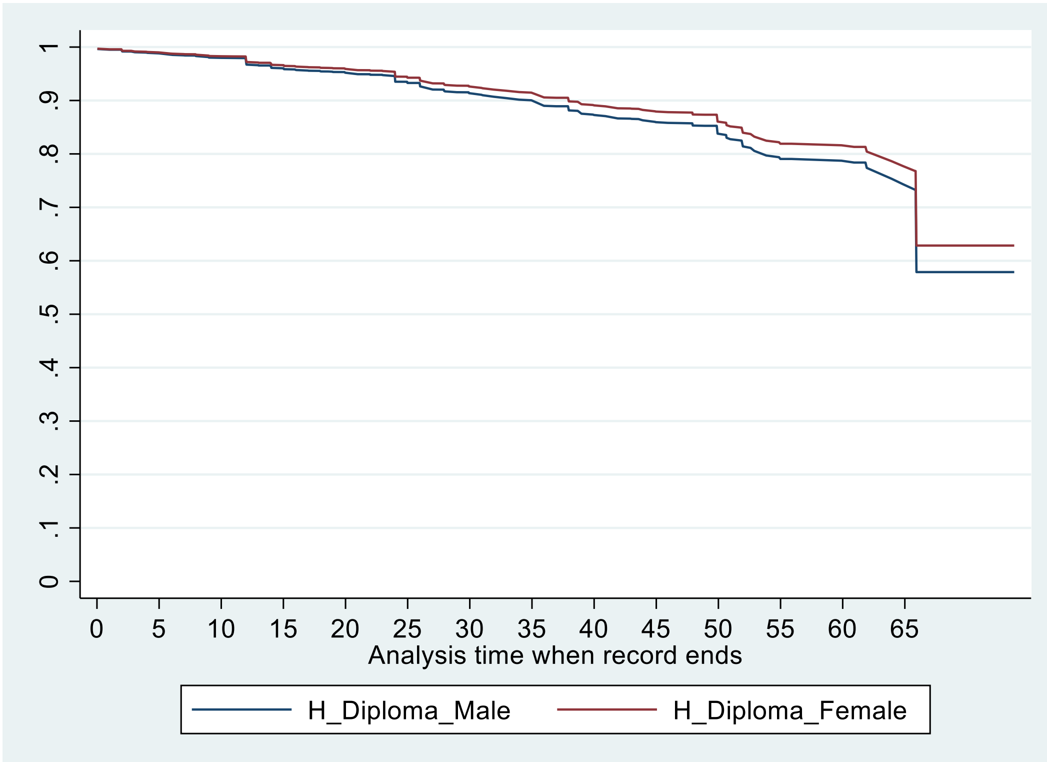

Figure 4:6 Survival Function Estimates for Higher Diploma

Figure 4.6 shows that male higher diploma graduate had a higher hazard rate compared to Higher diploma female graduate. The graphs of craft male and craft female and higher diploma male and diploma female have also been estimated in Fig.4.7 and Fig 4.8.

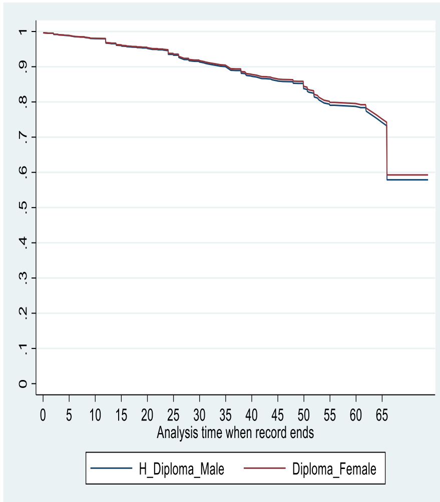

Figure 4.7: Survival Function for Diploma

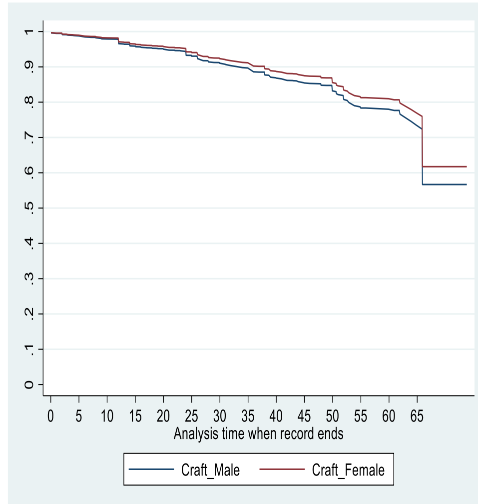

Figure 4.8: Survival Function for Craft by gender

The survival curves for the analysis shows a decline from left to right, indicating that the survival probability decreased over time. Specifically, the survival probability dropping to approximately 0.58 for higher diploma male and 0.62 for higher diploma female (figure 4.14) suggesting that, as time progressed, about 58% and 62% of respondents respectively remained in the non-failure/Unemployed at end of study period. This decline reflects the cumulative occurrence of time to employment. The survival curve revealed how different educational pathways impacted the time to event(employment). Censoring: A steep drop shows high number of censored observations when the study time ended. Figures 4.15 and 4.16 show that male hazard rate is higher than female.

4.5.5.6 Goodness of Fit

The study evaluated the fit of the final model by using the Cox-Snell residuals. The Nelson-Aalen cumulative hazard function and the cumulative survival variable graphs were drawn to compare the hazard function to the diagonal line. The hazard function followed the 45-degree line implying that it approximately had an exponential distribution with a hazard rate of one and that the model fitted the data well.

Model adequacy checking involved evaluating the statistical model to ensure it accurately represented the underlying data and met the assumptions necessary for reliable predictions and inferences. A Schoenfeld residual test was performed.

Schoenfeld Residual Test

The Schoenfeld residual test assessed the proportional hazards assumption in the Cox regression model. A non-significant global test p-value (p= 0.07) suggested no strong evidence against the proportional hazards assumption for all the predictors tested except for “Reservation2”. This implied that the relationship between the predictors and time remained relatively constant over time, which was in line with the assumptions of the Cox proportional hazards model.

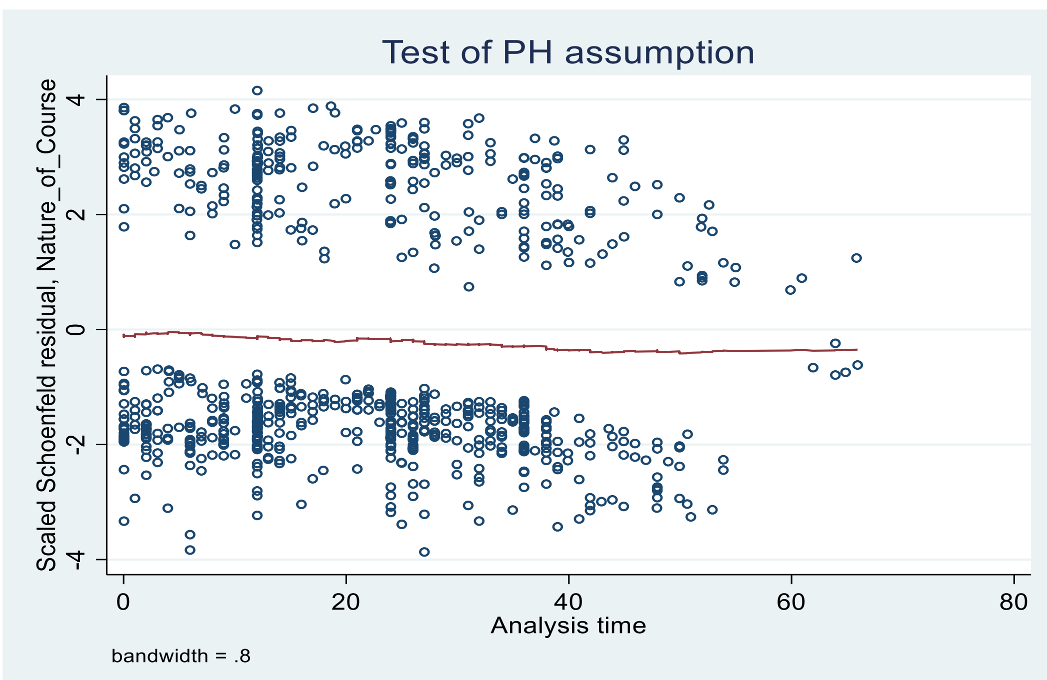

Figure 4:9 Test of PH Assumption

The residuals were randomly scattered around zero without any apparent pattern. This implied that the Cox model was correctly specified with the proportional hazards assumption holding. Additionally, the Cox-Snell residue graph was computed.

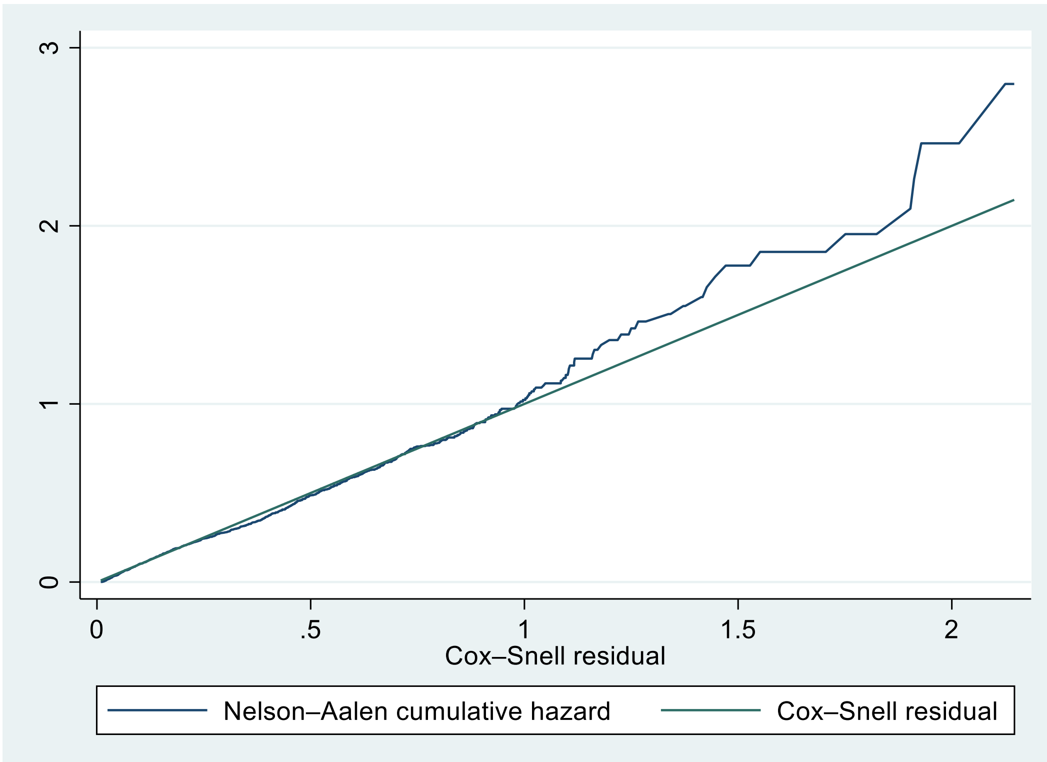

Figure 4:10 Cox Snell Residual Curve

The Cox-Snell residual curve is a diagnostic tool for assessing the fit of a Cox proportional hazards model. The residuals aligned with the reference line, suggesting a good model fit for the data.

4.5.6 Hypothesis Test

$H_0 2(d)$: The null hypothesis for this objective was that the level of STEM academic programs has no statistically significant effect on unemployment duration of graduates of national polytechnics in Kenya.

The study rejected null hypothesis at $\propto = 0.05$ and concluded that the level of certificate of STEM academic programs has a statistically significant effect on unemployment duration of graduates of national polytechnics in Kenya.

The interview with one of the registrars highlighted that;

"The *training programs for craft and diploma typically has lower barriers to entry compared to higher diploma thus allowing graduates to enter the workforce sooner."*

Another registrar said that;

"While academic qualifications are crucial, the skills students acquire are equally important. We frequently receive requests from companies seeking candidates with specific qualifications, and we often recommend students based on their performance. Therefore, achieving high academic standards can significantly enhance a graduate's chances of securing employment more swiftly."

The result further suggested that older respondents are more likely to transition from unemployment to employment, potentially due to accumulated work experience or a more targeted and persistent job search approach. This aligns with the findings of Neumark et al. (2019) and Jackson & Wilton (2017), who argue that older individuals may leverage their greater experience, maturity, and established networks to secure employment more quickly. Older job seekers often possess transferable skills, industry-specific knowledge, and professional maturity, which can enhance their attractiveness to employers. This experience, combined with a more strategic approach to job searching, may explain why older individuals experience shorter durations of unemployment compared to their younger counterparts.

Migrants experienced a slower transition to employment compared to non-migrants, suggesting that geographical mobility may present additional challenges such as adjusting to a new job market, cultural barriers, or a lack of local networks. This finding aligns with Koubi et al. (2016), who also observed that migrants often face delayed employment outcomes due to these factors. On the other hand, course duration emerged as a positive predictor of faster employment, implying that individuals who undergo longer courses might possess more comprehensive skills or qualifications that make them more attractive to employers. Longer training periods could lead to enhanced competencies, thereby increasing the likelihood of quicker job placements by providing graduates with a competitive edge in the job market.

The results show that respondents with a degree are 3.09 times more likely to transition to employment compared to those with lower qualifications, highlighting the advantage of higher education in securing jobs. This aligns with Wakeling & Laurison (2017), who found that degree holders are more attractive to employers due to their specialized skills and expertise. National polytechnics, which offer qualifications lower than a degree, face challenges in job market entry. For these graduates, the key to success lies in hands-on skills that meet the industry's specific needs, as practical experience often compensates for the lack of higher-level academic qualifications.

The survival analysis results indicate a significant gender disparity in the time to employment, with higher survival probabilities observed for males compared to females within both the higher diploma and craft qualification groups. This findings agree with Symeonaki & Filopoulou (2017) who argued that there exists gender-based differences in employment outcomes. These findings imply that men experience a shorter time to employment, potentially due to factors such as gender biases in hiring practices, differing societal expectations, or access to networks that facilitate faster job placement. This disparity underscores the importance of considering gender as a covariate in understanding employment trajectories, as it may influence the rate at which individuals move from unemployment to employment.

4.6 Academic Field of Study on Labour Market Outcomes

The third objective sought to establish the effect of academic field of study on labour market outcomes of graduates of national polytechnics in Kenya. The data were analysed and presented. The distribution of the field of study in percentages has been presented; a regression analysis has been conducted to examine the effect of academic field of study on earnings; a multinomial regression analysis has been employed to a assess the relationship between academic field of study and employment status; forth, a survival analysis has been performed using the semi paramedic Cox proportional hazards, and the Weibull parametric methods to analyse the time-to-event(Unemployment to employment). An estimation of the survival function with various scenarios has been done using the cox regression coefficients.

4.6.1 Descriptive Statistics of Field of Study.

The frequency of the eight fields of study have been presented in figure 4.11.

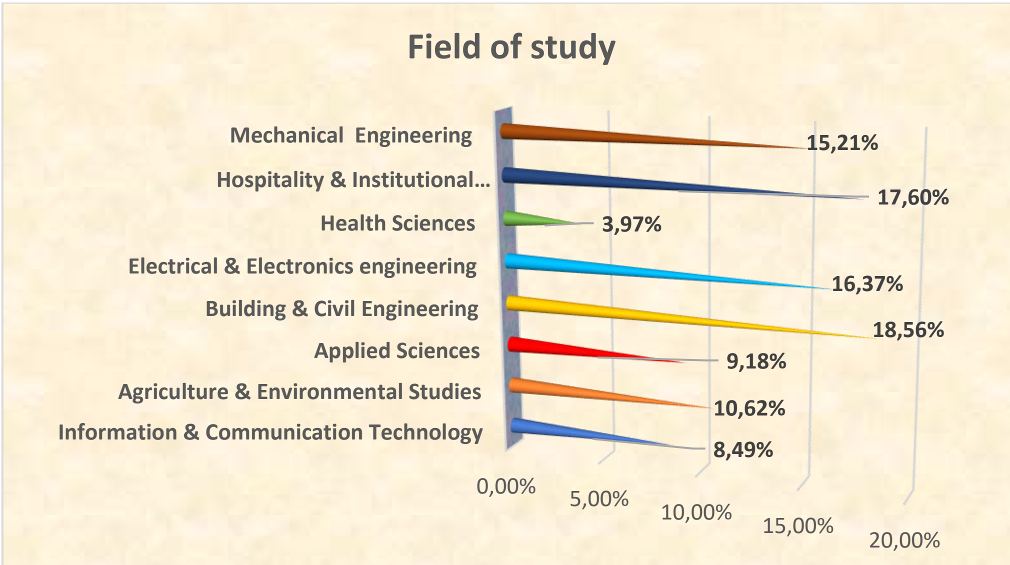

Figure 4.11 Field of Study

Building & Civil Engineering field had the highest enrolment (18.56%) while Health Sciences had the least (3.97%). The findings from the analysis of the fields of study provide valuable insights into the career aspirations and educational preferences of respondents. This information was crucial for academic sponsors and policymakers to tailor their support and resources effectively, ensuring that they align with the interests and demands of the students. By understanding these trends, academic programs can be better designed to meet the future needs of the job market and the development goals of the community.

The findings on the fields of study chosen by sponsored students align with global trends identified in past studies. There is a notable increase in enrolment in STEM fields, driven by the demand for technological and scientific skills (UNESCO, 2016). Humanities and social sciences remain valuable for fostering critical thinking and cultural awareness, although their growth is slower compared to STEM. Business and economics programs continue to attract students due to their applicability across industries (WEF, 2019; GMAC, 2019). The health and medical sciences fields are also seeing a rise in enrolment to address global health challenges (WHO, 2016) (ACGME, 2020). Lastly, education programs maintain steady interest as the need for quality educators persists (OECD, 2021; NCES, 2018). These trends underscore the importance of academic sponsorship in supporting students' educational and career aspirations across diverse disciplines.

4.6.2 Field of Study and Earnings

The table shows different levels of average total earnings on different predictor variables.

Table 4.37 Average Total Income for Specified Predictor Variables

Field of Study	**Mean Earnings**	**Std.err**	**[95%**	**conf.interval]**
ICT	13193.75	1857.844	9549.447	16838.05
Agriculture & Environmental Studies	13980.67	2939.89	8213.847	19747.49
Applied Sciences	11685.71	2297.55	7178.894	16192.53
Building & Civil Engineering	11078.97	1179.695	8764.912	13393.04
Electrical & Electronics engineering	13445.39	1660.646	10187.9	16702.87
Health Sciences	20603.59	4188.173	12388.16	28819.01
IM	10543.56	1169.18	8250.125	12837
Mechanical Engineering	11823.38	1894.027	8108.104	15538.66

Table 4:37 provides a statistical summary of various fields of study, presenting the mean, standard error, and 95% confidence interval for each. For ICT, the mean was Ksh. 13193.75 with a standard error of 1857.844. Agriculture & Environmental Studies had a higher mean of Ksh. 13980.67 but a larger standard error of Ksh. 2939.89, indicating more variability. Applied Sciences had a mean of Ksh. 11685.71, with a moderate standard error

of 2297.55. Building & Civil Engineering showed a mean earning of Ksh11078.97, with a relatively precise standard error of 1179.695 and a confidence interval of 8764.912 to 13393.04.

Electrical & Electronics Engineering had a mean earning of 13445.39, with a standard error of 1660.646 and a confidence interval from 10187.9 to 16702.87. Health Sciences stood out with the highest mean earning of Ksh. 20603.59 but also the largest standard error of 4188.173, indicating high variability and a wide confidence interval from 12388.16 to 28819.01. Information Management had a mean earning of Ksh.10543.56, with a standard error of 1169.18 and a confidence interval of 8250.125 to 12837. Mechanical Engineering’s mean earning of Ksh. 11823.38, with a standard error of 1894.027, and a confidence interval between 8108.104 and 15538.66.

Recent studies provide mixed support for the findings in table 4:38, which presents a statistical summary of various fields of study, including mean earnings, standard errors, and confidence intervals. Chetty et al. (2017) and Carnevale et al. (2015) support the high mean earnings and variability observed in fields like Health Sciences and Electrical & Electronics Engineering, highlighting significant earnings and variability in these areas due to job market demand and variability in job roles.

Conversely, Karmaeva & Ilieva-Trichkova, (2024) oppose the high variability in earnings for fields such as Health Sciences, arguing that standardized professional paths and regulatory frameworks often mitigate variability in high-earning fields, suggesting a need to reassess assumptions about earnings variability. These studies collectively underscore the complexity and diversity of earnings across different fields of study.

Analysis of Variance for Field of Study and Earnings

Table 4.38

Source	SS	df	MS	F	Prob > F
Between groups	2.02E+09	7	289196862	1.19	0.0306
Within groups	3.57E+11	1465	243437958		
Total	3.59E+11	1472	243655561		

The results from the one-way analysis of variance (ANOVA) show that there was a statistically significant difference in total earnings across different fields of study F (7, 1472) = 1.19, p= 0.0306. Additionally, Bartlett's test for equal variances suggests that the assumption of homogeneity of variances was not violated, $\chi2(7, N=1472) = 9.93$, p= 0.193 indicating that the variances were roughly equal across groups. A further analysis utilising a multiple regression analysis was performed.

4.6.2.1 Multiple Regression of Field of Study on Earnings

A multiple regression of the field of study on earnings was estimated. This analysis aimed to assess how different fields of study influenced earnings across multiple categories.

4.6.2. Regression Diagnostic Tests

A regression analysis was carried out with total earnings as the outcome variable. The predictor variable was field of study. Control variables included; Gender, migration_TO, AcadQual, CourseAdvance, jsi, Educsponsor, Examgrade, Marital_Status Migration_Dummy, ReservationWage2, Applications8wks and Scapital EmployCat.

The regression diagnosis (regcheck) test as proposed by Mehmetoglu (2014) was conducted to investigate for various assumptions underlying regression model. Firstly, the homoskedasticity assumption was scrutinized using the Breusch-Pagan test (Gujarati, 2012) with a significance level of 0.05 indicating heteroskedasticity. Secondly, multicollinearity was examined through Variance Inflation Factor (VIF) values (Studenmund, 2013) with values above 5.0 suggesting severe multicollinearity.

Thirdly, the normality of residuals was tested using the Shapiro-Wilk W test. The null hypothesis for normality holds true if p-value < 0.01. The null hypothesis is rejected at $p= 0.05$. Further, the Shapiro-Wilk W test is, like any other is not sensitive to large sample sizes. Fourthly, the correctness of model specification was evaluated via the linktest (Stata Manual), where a statistically significant _hatsq ($p < 0.05$) indicated a specification problem. Fifthly, the appropriateness of the functional form was assessed using Ramsey's regression specification error test (RESET) (Wooldridge, 2019). Lastly, influence, determined by leverage and outlier status, was examined using Cook's distance (D) (Pardoe, 2006), where observations with $D > 1$ were often considered influential and may have warranted removal from the analysis.

Table 4.39 Regression Diagnostic Test

Regression assumptions:	Test:	We seek values
1) Heterokedasticity problem	Breusch-Pagan hettest Chi2(1): 1829.063 p-value: 0.000	> 0.05
2) Multicollinearity problem	Variance inflation factor	< 5.00
Field_of_Study	2.32	
Gender	2.39	
migration_TO	3.99	
AcadQual	1.69	
Examgrade	2.54	
Marital_Status	2.87	
Migration_Dummy	19.18	
ReservationWage2	5.18	
EmployCat	1.12	
EmployCat	1.06	
EmployCat#c.Field_of_Study	1.48	
Field_of_Study	6.39	
Nature_of_Course	9.17	
A15_LevelofCert	6.64	
3) residuals are not normally distributed	Shapiro-Wilk normality test z: 15.242 p-value: 0.000	> 0.01
4) Specification problem	Linktest t: 7.642 p-value: 0.000	> 0.05
5) Functional form problem	Test for appropriate functional form F(3,1433):32.916 p-value: 0.000	> 0.05
6) No influential observations	Cook's distance	< 1.00

The results of table 4.39 showed that the regression equation had a heteroscedastic problem, specification problem, functional form problem and no influential observations. This led to the use of robust stepwise cox regression model. Applying the robust stepwise cox regression model, the model gave the results as shown in table 4.40.

Table 4.40 Stepwise Cox Regression Model

Total_Earnings	Coefficient	Std. err.	T	P>t
Field_of_Study				
Electrical & Electronics engineering	3948.07	1275.61	3.100	0.00
Health Sciences	6169.32	2461.07	2.510	0.01
Marital_Status				
Not Married	-1689.26	949.12	-1.780	0.08
EmployCat				
Employed in my field of study	3283.99	1801.99	1.820	0.07
In Training	-35509.70	3698.98	-9.600	0.00
employed in different field of study	-36564.54	1964.80	-18.610	0.00
Self-employed in field of study	-36939.12	2129.43	-17.350	0.00
Unemployed	-36913.22	1683.50	-21.930	0.00
Scapital	1385.70	979.83	1.410	0.16
Gender#c.Field_of_Study				
Female	-794.65	334.95	-2.370	0.02

Number of obs = 1,473 F(20, 1452) = 67.29
Prob > F = 0.0000 R-squared = 0.5364

The robust stepwise cox regression model explored the determinants of earnings, explaining 53.64% of the variance (R-squared = 0.5364) and being statistically significant overall (F (20, 1452) = 67.29, p < 0.001). Graduates in Electrical & Electronics Engineering earned Ksh. 3,948 more, and those in Health Sciences earned Ksh. 6,169 more compared to other fields, both statistically significant (p=0.002 and p=0.012, respectively). These results suggested a considerable advantage in earnings for certain technical and health-related fields.

Key findings indicate that Marital status showed a near-significant effect, with respondents who were not married earning, on average, Ksh. 1,689 less than their married counterparts, though this effect was not statistically significant (p=0.075). Employment category had a profound impact on earnings. Those in training, self-employed in a different field, self-employed in their field of study, and unemployed all earned significantly less, with reductions ranging from Ksh. 35,509 to Ksh. 36,939 ($p<0.001$ for all).

Gender interactions with the field of study highlighted disparities. Females earned Ksh. 795 less in their respective fields compared to males, with this difference being significant ($p=0.018$).

4.6.2. 1 Hypothesis test

$H_02(d)$: The null hypothesis for this objective was that the field of study has no statistically significant effect on earnings of graduates of national polytechnics in Kenya.

The study rejected null hypothesis at $\propto = 0.05$ and concluded that the field of study has a statistically significant effect on earnings of graduates of national polytechnics in Kenya.

These results indicate significant earnings advantage for graduates from technical and health-related fields, aligning with the findings of Kirkeboen et al. (2016) and Eide et al. (2016), who similarly highlighted that these fields often lead to higher-paying employment opportunities. This suggests that technical and health-related qualifications are in high demand and provide graduates with a distinct edge in the labour market.

Furthermore, the analysis suggested that females earned less in their respective fields compared to males, a result that supports the findings of Cheryan et al. (2017), who documented gender-based pay disparities across various industries. These results point to the persistence of gender pay gaps, even in fields where women are well-represented, highlighting the need for policies that address such inequalities in the workforce

Overall, the analysis underscores the significant roles of educational background, employment status, and demographic factors in influencing total earnings. There were significant income disparities across different fields of study. Fields that require technical expertise or are in high demand often offer higher salaries. Data from the Bureau of Labor Statistics (BLS) in the United States consistently show that STEM occupations tend to have higher median wages compared to non-STEM occupations (BLS, 2023). These results confirm that earnings of graduates vary significantly from person to person (OECD, 2015).

During an FGD, it emerged that;

"*Electrical engineering graduates often command higher wages because they provide essential services in a service industry. They are in constant demand by a broad segment of the population. Their expertise gives them significant bargaining power in their field. Additionally, the requirement for professional registration with Energy & Petroleum Regulatory Authority for all who practice makes their industry appear expensive. This trend is similar to that seen with health graduates, who also benefit from strong demand and greater leverage due to the critical nature of their services*." Interview with registrars further confirmed that *"graduates of health sciences courses had higher earnings because the risk involved in their service delivery*."

In conclusion, the findings highlight significant earnings advantages in technical and health-related fields, while also revealing persistent gender pay disparities that warrant attention

4.6.4 Field of Study and Employment Status

The relationship between the field of study and employment status was explored to understand how different fields impact various employment outcomes. Employment status categories included: employed in the field of study, employed in a different field of study, self-employed in the field of study, self-employed in a different field of study, and unemployed. This analysis aimed to reveal how the field of study influences career paths and employment scenarios. A multinomial logistic model was used for analysis

The employment category was a categorical variable comprising of respondents who were employed in; different field of study, own field of study, in training, unemployed, self-employed in different fields of study, and self-employed in their field of study.

4.6.5 Multinomial Logistic Regression on Factors Influencing Employment Status

The multinomial logistic regression model provided valuable insights into the factors influencing employment status categories relative to being unemployed. This analysis revealed several significant predictors that helped understand what drove respondents towards different employment outcomes. These predictors include; Field_of_Study, Gender, A10_Age, SpellDuration, Courseduration, migration_TO, AcadQual, Scapital, CourseAdvance, jsi, Educsponsor, Examgrade, Marital_Status, Migration_Dummy, ReservationWage2, and Applications8wks. Each category—employment in a different field, employment in the same field, training, and self-employment—had unique predictors that significantly impacted on the likelihood of being in that category. Table 4.43 gives a summary of statistically significant factors that determined the employment category.

Table 4.41 Multinomial Logistic Regression of Field of Study on Employment Status

Variable	Employed in different field of study				Employed in own field of study				in training				Self Employed in different field				Self-Employed in own field of study			
	coeff	Std Err	z	P>|z|	coeff	Std Err	z	P>|z|	coeff	Std Err	z	P>|z|	coeff	Std Err	z	P>|z|	coeff	Std Err	z	P>|z|
Field_of_Study	0.98	0.04	-0.6	0.567	0.96	0.03	-1.47	0.143	0.99	0.08	-0.18	0.853	0.93	0.03	-1.92	0.055	0.88	0.04	-3.06	0.002
migration_TO	1.83	0.28	3.99	0.000	2.05	0.24	6.22	0.000	1.11	0.37	0.32	0.752	1.56	0.21	3.3	0.001	1.72	0.25	3.66	0.000
AcadQual	1.20	0.15	1.48	0.138	1.40	0.13	3.6	0.000	2.72	0.82	3.3	0.001	1.03	0.11	0.24	0.808	1.06	0.13	0.46	0.648
CourseAdvance	1.17	0.27	0.67	0.501	1.64	0.26	3.14	0.002	4.21	1.36	4.44	0.000	0.93	0.20	-0.34	0.733	1.29	0.27	1.18	0.237
jsi	1.50	0.17	3.54	0.000	1.17	0.10	1.79	0.073	1.07	0.24	0.29	0.770	1.54	0.15	4.36	0.000	1.05	0.12	0.4	0.691
Educsponsor	0.94	0.11	-0.5	0.625	0.90	0.08	-1.31	0.189	1.31	0.38	0.94	0.349	0.99	0.10	-0.07	0.944	0.84	0.08	-1.75	0.080
Examgrade	1.03	0.07	0.35	0.727	0.89	0.05	-2.18	0.029	1.09	0.16	0.58	0.564	1.07	0.07	1.09	0.277	1.00	0.07	0.03	0.980
Marital_Status	1.02	0.20	0.11	0.909	1.43	0.21	2.38	0.017	0.23	0.10	-3.41	0.001	0.77	0.13	-1.58	0.114	1.25	0.25	1.12	0.263
Migration_Dummy	0.79	0.18	-1	0.297	0.74	0.12	-1.84	0.066	0.62	0.29	-1.02	0.307	1.06	0.20	0.33	0.741	1.27	0.26	1.13	0.258
ReservationWage2	1.00	0.00	-1	0.303	1.00	0.00	-1.27	0.205	1.00	0.00	-0.02	0.984	1.00	0.00	-1.35	0.176	1.00	0.00	-1.44	0.149
Applications8wks	0.81	0.06	-2.9	0.004	0.85	0.04	-3.38	0.001	0.90	0.12	-0.82	0.412	0.91	0.05	-1.75	0.079	0.95	0.06	-0.79	0.432
_cons	0.02	0.03	-2.8	0.006	0.03	0.03	-3.31	0.001	0.00	0.00	-3.14	0.002	0.10	0.12	-1.93	0.053	0.20	0.26	-1.22	0.221
Base outcome: Unemployed																				

Note. The base outcome variable is Unemployed. _cons estimates baseline relative risk for each outcome.

The results of the multinomial logistic regression analysis demonstrate that field of study was predictor in determining the likelihood of employment outcomes, though its influence varied depending on the specific employment category.

Employed in a Different Field of Study

With regard to individuals employed in a different field of study, the field of study was not statistically significant (RRR = 0.9757, p = 0.567), suggesting that field-specific education did not significantly affect the likelihood of transitioning into a job outside one's area of study. This suggests that the field of study did not significantly influence the likelihood of being employed in a different field. However, other variables, such as migration and job search intensity (JSI), significantly affect this outcome. Geographical mobility (MigrationTo) increased the likelihood of being employed in a different field by 82.85%, while JSI increases the likelihood by 50.24%. An increase in the number of job applications by one decreased the likelihood of being employed in a different field by 18.86%.

Employed in Own Field of Study

The field of study was not a significant predictor in determining employment in own field of study (RRR = 0.9556, p= 0.143). However, other variables showed significant effects. Geographical mobility (MigrationTo) increased the likelihood of being employed in the same field by 104.97%, while academic qualifications raise the likelihood by 39.84%, and course advancement increased it by 64.16%. On the other hand, exam grades negatively influence employment in the same field, decreasing the likelihood by 10.89%.

In Training

In the In Training category, field of study was not significant (RRR= 0.9855, p= 0.853. However, academic qualifications and course advancement were highly significant($p<0.05$). Academic qualifications increased the likelihood of being in training by 171.76%, and course advancement increased the likelihood by 321.37%, suggesting that further education and progress in academic studies strongly encourage participation in training. Additionally, marital status had a significant negative effect, decreasing the likelihood of being in training by 77.11%.

Self-employed in a Different Field of Study

The field of study was not a significant determinant of employment in different Field category (RRR= 0.9319, p= 0.055) compared to being unemployed. While marginally non-significant, migration significantly increased the likelihood of self-employment in a different field by 55.65%, and JSI raised the likelihood by 53.65%. These findings suggest that individuals who migrate or engage in higher job search activity are more likely to be self-employed in a field outside their study area. Applications in the past 8 weeks decrease the likelihood by 9.28%, although this result were not as significant.

Self-employed in Field of Specialization

In the Self-employed in Field of Specialization category, field of study was a significant predictor (RRR= 0.8819, p= 0.002), suggesting a 11.81% decrease in the likelihood of being self-employed in one's specialized field compared to being unemployed. This suggests that individuals with certain fields of study are less likely to be self-employed in their specialized field, potentially due to a mismatch between their education and available entrepreneurial opportunities. Migration played a significant role, increasing the likelihood of self-employment in a own field of study by 71.72%. Other variables such as job search intensity and applications in the past 8 weeks do not show significant effects.

In summary, field of study is not a significant predictor in the employed in a different field and employed in own field of study categories, suggesting that employment outcomes in these areas are influenced more by other factors, such as migration, academic qualifications, and course advancement. However, field of study is a significant predictor in the self-employed in field of specialization category, indicating that certain fields of study may limit opportunities for self-employment in specialized fields. In contrast, migration and academic qualifications consistently emerge as strong predictors across the categories, particularly for being employed in the same field, in training, or self-employed in a different field.

Hypothesis testing

$H_0 2(d)$: The null hypothesis for this objective was that the field of study has no statistically significant effect on employment status of graduates of national polytechnics in Kenya.

The study rejected null hypothesis at $\propto = 0.05$ and concluded that the field of study has a statistically significant effect on employment status of graduates of national polytechnics in Kenya.

The findings that field of study is not a significant predictor in the Employed in a Different Field and Employed in Own Field of Study categories align with the perspective of Di Paolo & Matano (2022), who argue that pre-graduation work activities related to the field of study are more influential for employability and job stability than the field of study itself. This suggests that practical experience, such as internships and job placements, may play a more crucial role in determining employment outcomes than the academic discipline.

Additionally, the increasing emphasis on transferable skills and the flexibility of the labour market, where individuals can move across different fields based on competencies rather than strictly their field of study, likely contributes to the lack of significance for field of study in these categories. Other factors like migration patterns, academic qualifications, and job search intensity may also overshadow the direct impact of field of study on employment outcomes.

The findings that field of study is a significant predictor in the Self-Employed in Own Field of Specialization category suggest that the academic discipline a person graduates in can significantly impact their likelihood of becoming self-employed within their specialized field. This indicates that certain fields may offer more opportunities for self-employment within specific niches, while others may face limitations.

Montt (2017) notes that the saturation of a particular field in the labour market can restrict the ability of graduates to enter self-employment in their specialization, as the market may already be flooded with individuals offering similar services. Moreover, the transferability of skills across different industries also plays a crucial role in this dynamic. Fields with highly transferable skills may allow for a broader range of entrepreneurial opportunities, whereas specialized fields with less transferable skills may limit graduates' options for self-employment in their chosen area.

The incidence of field-of-study mismatch and overqualification also becomes relevant here, as individuals with specialized training may struggle to find employment that matches their qualifications, potentially pushing them into self-employment. These findings underscore the importance of considering labour market saturation and skill transferability when assessing the relationship between field of study and self-employment.

4.6.6 Field of Study and Sector Employed

The study analysed the sectors that were predominantly employers of TVET graduates. Of the 461 employed, 213 were employed in private sector while 248 were employed in public sector. To ensure the robustness of logistic regression model, several diagnostic tests were performed. The Hosmer-Lemeshow test (estat gof) assessed the model fit by comparing observed and expected event rates (Hosmer & Lemeshow, 2000). Multicollinearity was evaluated using the Variance Inflation Factor (VIF) which identified existence of inflated standard errors due to correlated predictors (O'Brien, 2007). Cook's distance (predict cooksd) helped detect influential observations that might have disproportionately affected the model (Cook & Weisberg, 1982). Additionally, the linktest command evaluated whether the model appropriately captured the linear relationship between predictors and the logit (Pregibon, 1980). These diagnostics collectively ensured that the logistic regression analysis was valid and reliable. The table 4.44 shows the results.

Table 4.42 Table Logistic Regression

Logistic regression				**Number of obs**	**460**
				LR chi2(2)	43.21
				Prob > chi2	0
Log likelihood = -296.38773				Pseudo R2	0.0679
Goodness-of-fit test after logistic model					
Hosmer–Lemeshow chi2(8) =	5.59				
Prob > chi2 =	0.6928				
Sensitivity	Pr(+ D)	72.40%			
Specificity	Pr(-~D)	49.77%			
Correctly classified		61.88%			
Linktest results					
SectorEmpl Coefficient	Std. err.	z	P>z	[95% conf.	interval]
_hat	1.02187	0.174	5.87	0.000	0.68083
_hatsq	-0.1032	0.2023	-0.51	0.610	-0.4998
_cons	0.03386	0.1194	0.28	0.777	-0.2004
Pearson Chi-Square Test					
Pearson chi2(444) =	341.81				
Prob > chi2 =	0.1618				

The diagnostic tests for the logistic regression model predicting sector employed indicated a generally well-fitting model. The Hosmer-Lemeshow test suggested that the model's predicted probabilities aligned well with the observed outcomes, (χ^2(1, 807) = 5.59, p= 0.6928. The classification table showed a sensitivity of 72.40% and a specificity of 49.77%, with an overall correct classification rate of 61.88%, reflecting moderate predictive performance. The linktest results, where the linear term _hat is significant but the squared term _hatsq is not, suggested the model was appropriately specified without evidence of model misfit. Additionally, the Pearson chi-square test further supported the model fit with no significant discrepancies between observed and expected values(χ^2(1,

807) = 341.81, p= 0.1618. Overall, these diagnostics collectively indicated a reasonably well-fitting logistic regression model.

Table 4.43 Binary Logistic Regression of Field of Study and Employment Sector

SectorEmpl Public Sector	**RRR**	**St.Err.**	**t-value**	**p-value**	**[95% Conf**	**Interval]**
Field_of_Study	.966	.042	-0.79	.427	.886	1.053
Gender	.692	.152	-1.68	.094	.449	1.065
Marital_Status	.587	.132	-2.37	.018	.378	.912
A10_Age	1.076	.038	2.04	.041	1.003	1.154
Examgrade	.778	.059	-3.29	.001	.67	.904
A25Application8WKS	.982	.041	-0.43	.669	.905	1.066
CourseAdvance	1.343	.295	1.34	.18	.873	2.067
AcadQual	.843	.112	-1.28	.199	.649	1.094
Constant	.926	1.589	-0.04	.964	.032	26.739
Mean dependent var	1.530		SD dependent var			0.500
Pseudo r-squared	0.071		Number of obs			438
Chi-square	42.818		Prob > chi2			0.000
Akaike crit. (AIC)	590.834		Bayesian crit. (BIC)			647.985
Base output: Private Sector						

The binary logistic regression analysis explores the predictors of employment sector choice, with a focus on discerning factors that influence respondents' likelihood of being employed in the "Public" sector compared to the "Private" sector. Among the variables examined, Marital_Status emerged as a statistically significant predictor, with a relative risk ratio (RRR) of 0.5871334 and a p-value of 0.018. This implied that being married decreased the likelihood of working in the public sector by approximately 41.29% compared to being in the private sector. The negative association between marital status and employment in the public sector underscores the importance of considering personal demographics in understanding sector-specific employment patterns.

Each additional year of age increased the likelihood of being employed in the public sector by about 7.56% compared to being in the private sector(RRR= 1.076, P= 0.041). This positive association between age and public sector employment suggests a potential preference for older respondents within public sector roles, perhaps influenced by factors such as experience or stability. Moreover, Examgrade higher exam grades decrease the likelihood of being employed in the public sector by approximately 22.18%, compared to being in the private sector indicating a preference for respondents with superior academic performance in private sector roles ($RRR = 0.77$, $p < 0.001$).

However, several other variables in the model, such as field of study, gender, geographical mobility, job search intensity, job applications and academic qualification did not exhibit statistically significant associations with employment sector choice ($p > 0.05$).

Overall, the significant results emphasize the influence of personal demographics and academic performance on sector-specific employment outcomes, providing valuable insights for policymakers and stakeholders in understanding and addressing workforce dynamics.

Hypothesis testing

$H_0 2(d)$: The null hypothesis for this objective was that the field of study has no statistically significant effect on the sector of employment of graduates of national polytechnics in Kenya.

The study did not reject null hypothesis at $\propto = 0.05$ and concluded that the field of study has no statistically significant effect on the sector of employment of graduates of national polytechnics in Kenya.

One of the registrars pointed out that;

"Training programs prepare learners for employment in both public and private sectors by focusing on core skills such as problem-solving, communication, and critical thinking, which are valuable across all job roles. The training programs also incorporates industry-specific knowledge and practices relevant to both sectors, including an understanding of regulatory environments and business practices. Additionally, practical experience is a key component, with internships, project work, and simulations providing exposure to real-world scenarios and sector-specific challenges. This combination ensures that learners are adaptable and well-equipped for various career opportunities."

The study's findings suggest that being married decreases the likelihood of working in the public sector, a finding that aligns with Feeney & Stritch (2019). Married individuals may face different economic or social pressures that influence their career choices, potentially leading them to prefer employment in sectors that offer greater work-life balance or flexibility, such as the private sector. This could be further influenced by factors like family responsibilities. Additionally, the study highlights that women are more likely to work in sectors with a higher gender wage gap, a phenomenon also observed by Ray & Pana-Cryan (2021). This is consistent with the findings of Fletcher et al. (2017), which note that women tend to be employed in sectors where wage disparities, often linked to gender discrimination, are more pronounced. These dynamics underline the intersection of gender, marital status, and sectoral employment choices, where structural inequalities may shape individuals' career paths and opportunities.

The study's results suggest that successful outcomes in securing employment were largely attributed to the job application workshop and transport subsidy treatment, which were designed to reduce the costs associated with job searching. This aligns with Abebe et al. (2021), who emphasize the importance of reducing financial and logistical barriers to improve job-seeking success. By providing these resources, individuals were better equipped to navigate the job market, leading to higher employment outcomes

4.6.7 Survival Analysis: Field of Study and Unemployment Spell

The final part of this third objective was to analyse the field of study on unemployment spell using the survival model. This analysis sought to establish the time it takes (in months) for TVET graduates to find employment (time to event). The analysis used, semi-parametric tests, and parametric tests to model these survival functions. Results of the analysis were compared and conclusions made. Predictor variables were; Field of study. Control variables included; Applications8weeks, Sector, A8: MigrateTo, Total Earnings, Mean Total Earnings, A4: Gender, A10: Age, A13: StudyField, A8: MigrateTo, JSI, A11: EducSponsor, Reservation wage, A15: LevelStartCourseCode, A16: Highest Qualification, and Exam Grade.

4.6.8 Description of Data

Table 4.47 presents median survival time for the level of certificate.

Table 4.44 Median Survival Time

Field of Study	Time at risk	Incidence rate	Number of Subjects	------ Survival time…. 25%	50%	75%
ICT	3,307.08	0.0205	112	15.93	31.93	53.86
Agriculture	4,371.51	0.0205	147	14.03	35.96	.
Applied Sciences	4,297.97	0.0176	139	18.98	35.96	.
Building & Civil	9,293.15	0.0188	299	15.05	35.96	61.93
Electrical	7,647.21	0.0166	241	19.93	41.90	65.93
Health Sciences	1,592.26	0.0207	58	18.62	29.93	.
IM	8,662.10	0.0144	263	23.96	44.91	.
Mechanical & Automotive	6,671.93	0.01468	199	23.96	41.90	.
Total	45,843.212	.0172763	1458	18.03	37.96	65.9

The median time to employment, given in months, represents the point at which 50% of respondents from each field have secured employment. For the Information Technology field of study, the median time to employment was 31.93 months (95%CI: 30.33-33.53), indicating that half of the IT graduates find employment within approximately 32 months. In Agriculture, the median time to employment was 35.97 months, meaning half of the agriculture graduates secure jobs within approximately 36 months. In the Applied Sciences field, the median time to employment was 35.97 months (95%CI: 30.33-33.53) showing that 50% of applied sciences graduates found employment within the same period.

The median time to employment for the Building and Civil engineering field was 35.97 months (95%CI: 30.33-33.53), with half of the graduates employed within this timeframe. In Electrical Engineering, the median time to employment was 41.90 months, (95%CI: 30.33-33.53), indicating a longer duration for half of the electrical engineering graduates to find jobs. The Health Sciences field of study had a median time to employment of 29.93

months (95%CI: 30.33-33.53), showing that half of the health sciences graduates secure employment within approximately 30 months. In hospitality and institutional management, the median time to employment was 44.92 months (95%CI: 30.33-33.53), indicating that half of the hospitality graduates found jobs within this period. The Mechanical Engineering field of study had a median time to employment of 41.90 months (95%CI: 30.33-33.53), showing that half of the mechanical engineering graduates are employed within this timeframe.

Overall, the total median time to employment across all fields of study is 37.97(95%CI: 39.81-44.00) months. This indicated that, on average, respondents from all fields of study secure employment within approximately 38 months. The variation in median times to employment highlights differences in job market dynamics across different fields, with some fields like Health Sciences showing a quicker path to employment compared to fields like Hospitality and Electrical Engineering.

The study sought to examine the relationship between field of study and unemployment duration. To assess these relationships, the study used the Log-Rank Test. The Log-Rank Test: Equality of Survivor Functions compared survival functions across fields of study, testing if there were significant differences in the time to specific employment outcomes based on field of study. This test was useful in survival analysis, helping determine if the "survival" (or success) rate of employment outcomes differed significantly between groups with varying fields of study. Table 4.45 Shows the results.

Table 4.45 Log-Rank Test: Equality of Survivor Functions

Field of Study	Observed events	Expected Events
Information & Communication Technology	68	57.06
Agriculture & Environmental Studies	90	75.9
Applied Sciences	76	73.56
Building & Civil Engineering	175	160.16
Electrical & Electronics Engineering	127	132.2
Health Sciences	33	27.28
Hospitality & Institutional Management	125	150.26
Mechanical Engineering	98	115.58
Total	792	792
	chi2(7)	14.9
	Pr>chi2	0.0372

The log-rank test for equality of survivor functions across different fields of study showed a statistically significant difference in survival times, ($\chi^2(7, 1466) = 14.9$, $p = 0.0372$). For instance, the Building & Civil Engineering field observed 175 events against an expected 160.16, while Hospitality & Institutional Management observed 125 events against an expected 150.26. This revealed variability in survival times across different academic disciplines. A seme parametric analysis using the Cox proportional hazard was utilized to establish the effect of field of study and other control variables on the time to event(employment).

4.6.10 Semi-Parametric Method: Cox Proportional Hazard Function

The Cox proportional hazard function examined the relationship between the survival time of graduates' field of study. The function assumes that the effect of the predictor variables on the hazard rate was multiplicative and remained constant over time. This method was preferred because it handled multiple covariates simultaneously, allowing for a more comprehensive understanding of the factors influencing survival. The proportional-hazards assumption test for a Cox proportional hazards model evaluated whether the covariates in the model had hazard ratios that remained constant over time. Table 4.46 shows the results of the proportionality assumption test.

Table 4.46 Test of Proportional-Hazards Assumption

Variable	**Rho**	**chi2**	**Df**	**Prob>chi 2**
Field_of_Study	-0.055	2.300	1	0.130
Gender	0.016	0.190	1	0.663
Migration_Dummy	0.020	0.300	1	0.583
Courseduration	-0.009	0.060	1	0.808
Marital_Status	0.028	0.620	1	0.432
A10_Age	0.036	0.960	1	0.327
Examgrade	-0.068	3.390	1	0.066
Jsi	0.077	4.710	1	0.030
Scapital	-0.048	1.880	1	0.171
CourseAdvavance	0.069	3.650	1	0.056
ReserveWage2	-0.057	2.510	1	0.113
Applications8weeks	0.011	0.100	1	0.748
Applications4weeks	0.035	1.040	1	0.309
AcadQual	-0.044	1.440	1	0.230
Global test		31.17	15	0.008

The test of the proportional-hazards assumption evaluated whether the effect of each covariate on the hazard rate remained constant over time, which was crucial for the validity of the Cox proportional hazards model. Most covariates, including Field_of_Study, Gender, Migration_Dummy, Courseduration, Marital_Status, A10_Age, Scapital, ReservationWage2, Applications8wks, A24Whatisthenumberofjoba, and AcadQual, did not show significant evidence against the proportional-hazards assumption and therefore did not vary over time($p > 0.05$).

The covariate JSI was statistically significant thus violating the proportional-hazards assumption ($p = 0.0300$). This implied that the relationship between job satisfaction index and the hazard rate varied over the analysis period. The global test, which considered all covariates simultaneously, yielded a significant violation of the proportional-hazards assumption overall $\chi^2(15, 1472) = 31.17$, $p = 0.0083$. This result suggested that at least one covariate's effect on the hazard rate was not constant over time.

The significant time-varying effect of the jsi variable contributed to this violation, indicating a need for model adjustments, such as including time-varying covariates or exploring alternative modelling approaches to address these variations. Following this violation, the study adopted the Cox Proportional Hazards Model with Time-Dependent Covariates (Tian, Zucker & Wei, 2005).

Table 4.47 Cox Proportional Hazards Model with Time-Dependent Covariates.

Variable	**Haz. ratio**	**Std. err.**	**z**	**P>z**
Field_of_Study	0.9782	0.015074	-1.43	0.152
Gender	1.1767	0.089917	2.13	0.033
Migration_Dummy	1.2461	0.097648	2.81	0.005
Courseduration	1.0424	0.005926	7.3	0.000
Applications4wks	0.9527	0.018945	-2.43	0.015
AcadQual	1.1387	0.106783	1.38	0.166
Applications8wks	1.167	0.033193	-3.19	0.001
Examgrade	1.0778	0.054912	1.47	0.142
CourseAdvance	0.8533	0.140622	-0.96	0.336
Time variant covariates				
Jsi	1.0059	0.001623	3.62	0.000
Applications8wks	1.0032	0.001168	2.72	0.006
CourseAdvance	1.0125	0.005606	2.24	0.025
Examgrade	0.996	0.001872	-2.14	0.032
AcadQual	0.9984	0.003128	-0.52	0.606

The analysis of the hazard ratios from table 4.47 revealed the significance of several variables on the outcome of finding employment. First, focusing on the main effects, Gender, Migration_Dummy, Courseduration, Applications4wks, and Applications8wks were significant. Gender had a hazard ratio of 1.1765 ($p = 0.033$), implying that males had a 17.65% higher probability of finding employment compared to females. Migration_Dummy, with a hazard ratio of 1.2505 ($p = 0.004$), indicated that migrants had a 25.05% higher probability of finding employment compared to non-migrants.

The duration of the course (Courseduration) was highly significant with a hazard ratio of 1.0462 ($p < 0.001$), suggesting that each additional unit of course duration increased the probability of finding employment by 4.62%. Similarly, Applications8wks had a hazard ratio of 1.167 ($p = 0.000$), indicating that an increase in the number of jobs applied for increased the probability of finding employment by 16.7%.

On the other hand, some variables were inversely associated with finding employment. Applications4wks showed a significant effect with a hazard ratio of 0.9527 ($p = 0.015$), suggesting that more applications within the last four weeks decreased the probability of finding employment by 4.73%. These findings highlighted the importance of active job search efforts in reducing the probability of finding employment.

In the time-varying covariates (tvc), job search intensity (jsi), Applications8wks, CourseAdvance, and Examgrade showed significant results. Job search intensity (jsi) had a hazard ratio of 1.0059 ($p < 0.001$), implying that a high job search intensity slightly increased the probability of finding employment. Applications8wks had a hazard ratio of 1.0034 ($p = 0.002$), indicating a similar small increase in the probability of finding employment over time. CourseAdvance also had a positive hazard ratio of 1.0128 ($p = 0.021$), suggesting that advancing in the course slightly increased the probability of finding employment. Interestingly, Examgrade had a hazard ratio of 0.9960 ($p = 0.035$), indicating that better exam grades slightly decreased the probability of finding employment over time.

Lastly, some variables did not show significant associations with time to finding employment. Field_of_Study had a hazard ratio of 0.9758 ($p = 0.111$), indicating a non-significant effect. CourseAdvance in the main effects had a hazard ratio of 0.8502 ($p = 0.321$), suggesting no significant impact on the probability of finding employment.

Examgrade in the main effects also had a non-significant hazard ratio of 1.0735 ($p = 0.164$). These non-significant findings suggested that these factors might not play a crucial role in affecting the probability of finding employment in this particular dataset. Overall, the analysis highlighted the importance of gender, migration status, course duration, job application efforts, and job search intensity in influencing the probability of finding employment, with specific factors either increasing or decreasing the probability.

4.6.11 Model Estimation

The Cox proportional hazards model investigated the relationship between predictors and the time-to-event(employment) through the hazard function. It assumed that the predictors had a multiplicative effect on the hazard and that this effect was constant over time.

The general hazard function was given by:

$$h(t\backslash x) = h0(t)e\beta_1 X_1 + \ldots \beta_n X_n) \ldots\ldots\ldots\ldots\ldots\ldots\ldots \textbf{(4.6.1)}$$

The baseline survival function for the covariate pattern where all predictors were set to zero was estimated. The resulting baseline survival function((surv0) was;

$$\text{Surve}\ (0) = h\ (t\backslash x) = h0(t)e0 = h0(t) \ldots\ldots\ldots\ldots\ldots\ldots\ldots (4.\textbf{6.2)}$$

The predictor variables were; i.Field of study i.Gender i.Migration_Dummy CourseDuration, A10_Age, i.Examgrade, i.jsi, i.CourseAdvance, Applications8wks, A24Whatisthenumberofjoba and i.AcadQual.

Given the coefficients as computed, the resulting baseline hazard function was;

$$h(t\backslash x) = h0(t)e0 = (surv0) = h0(t)e\ {-.3084956X1} + .1632097X2 + .201762 + .036596X3 + 0.0241463X4 + .2524583X5 - .0499876X6 + -.0499876X7 \ldots\ldots\ldots \textbf{(4.6.3)}$$

Setting all predictors to zero;

$h(t\backslash x) = \forall x=0, h0(t)e0 = h0(t)(1) = h0(t)= (surv0)$ ………………………. **(4.6.4)**

In order to graph the survival functions, an estimate of the values of the covariates in the covariate pattern of interest was done.

Assume a graduate of the department of agriculture and had a craft certificate level (Level =2), Migrated (Migration Dummy=1), was male (Male=2), 30 years old, had a course duration of 2 years, had high job search intensity, and the exam grade, and made 10 applications in 4 weeks.

The survival function would be;

h(t\x) = h0(t)e0 = (surv0)

= h0(t)e -.3896063X1 + .1632097X2 +.201762 + .036596X3 +0.0241463(30) + .2524583X5 -.0499876X6 -.0499876Application4weeks......................................(4.6.5)

= h0(t)e - 0.3896063Craft+ 0.1632097Male + 0.201762Migration + 0.036596CourseDuration + 0.0241463Age + .2524583ExamGrade - 0.0499876jsi - 0.0499876X7 ……..............……………………………………………………….… (6)

The resulting survival function estimated will be;

h(t\x) =h1(t)= Surv(0)e -.3896063Craft+ .1632097Male +.201762Migration +.036596CourseDuration+ 0.0241463Age +.2524583ExamGrade -.0499876jsi - .0499876X7 ………………………………………………………………….. (7).

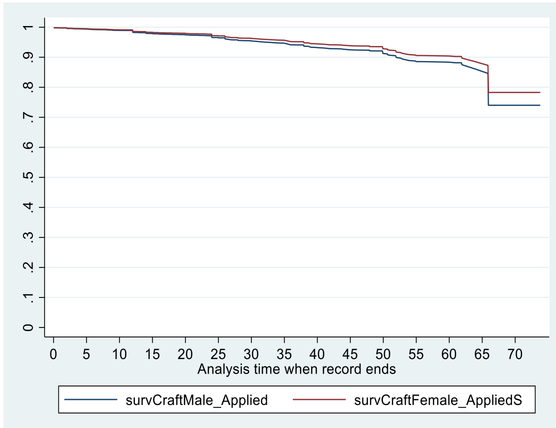

Figure 4:12 K-M Survival Function- Applied Sciences

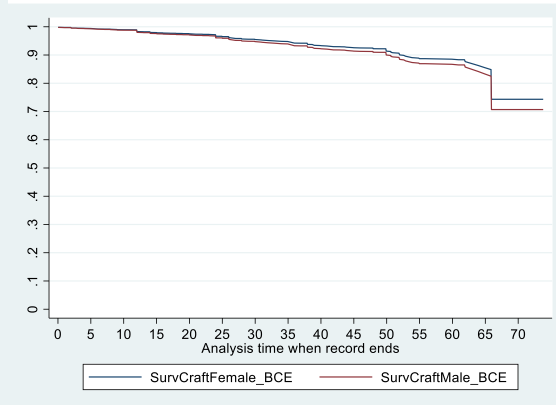

Figure 4.13 K_M Function- Building & Civil Source

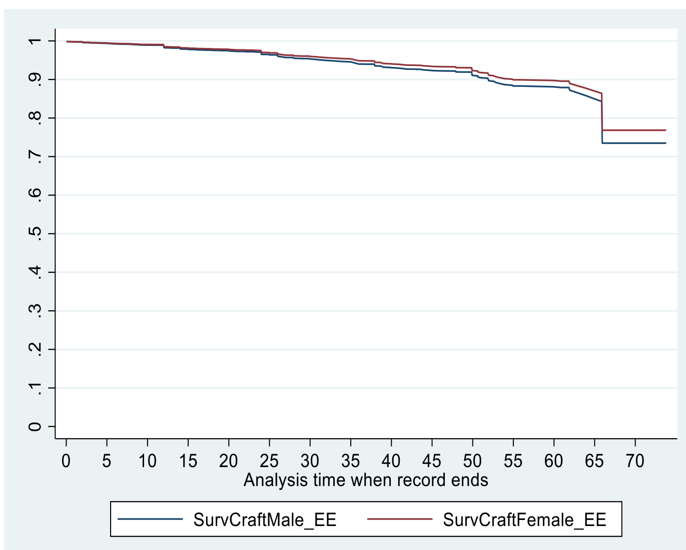

Figure 4:14 K_M Survival Function- Electrical & Electronics

Model Adequacy Checking

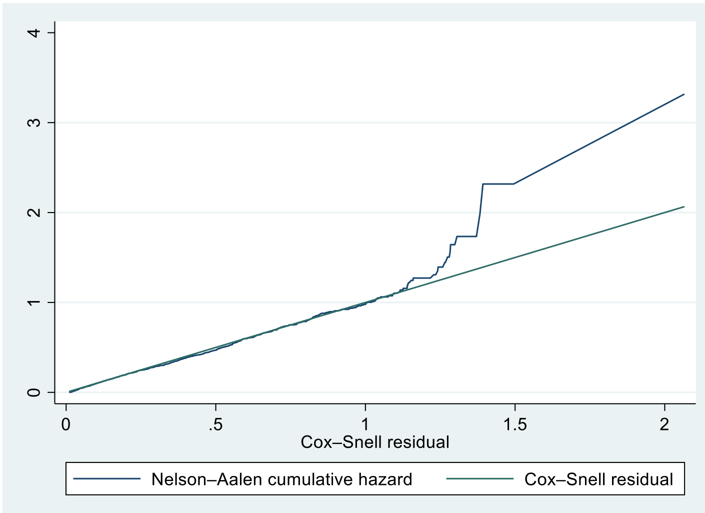

Figure 4:15 Model Adequacy

The Cox-Snell residual curve assessed the fit of a Cox proportional hazards model. The residuals aligned with the reference line, suggesting a good model fit for the data.

4.6.12 Parametric Tests for Field of Study

Parametric tests, including the Weibull, exponential, and Gompertz models, were used to analyse the unemployment spell as the response variable, with the field of study as the predictor variable. These tests made specific assumptions about the distribution of the data and aimed to evaluate hypotheses and make inferences about the relationship between the unemployment spell and the field of study including control variables. After conducting both non-parametric and semi-parametric tests, these parametric models were employed to determine whether they provided greater statistical power and precision.

The coefficients of the Gompertz, Weibull, Exponential and Cox regression models were estimated. The resulting AIC and BIC values are shown in table 4.50

Table 4.48 Model Selection Indices Using Several Parametric Distributions

Model	**AIC**	**BIC**
Weibull	3754.828	3907.282
Exponential	3755.857	3913.567
Gompertz	**3721.698**	**3879.408**
Cox	10303.68	10450.87

The true distribution of time to event often was unknown. Several parametric distributions were fitted during data analysis for comparison. The parametric distributions used included the Weibull, exponential, Gompertz, and Cox distributions. Model selection from candidate variables was accomplished by minimization of the Akaike and Bayesian information criteria (AIC and BIC). The Gompertz distribution met the AIC and BIC conditions for selection.

Table 4.49 Gompertz Coefficients

_t	Coefficient	Std. err.	z	P>z
Field_of_Study				
Agriculture & Environmental Studies	0.121	0.163	0.74	0.458
Applied Sciences	-0.071	0.168	-0.4	0.674
Building & Civil Engineering	-0.027	0.145	-0.2	0.854
Electrical & Electronics engineering	-0.097	0.153	-0.6	0.528
Health Sciences	0.056	0.215	0.26	0.794
IM	-0.152	0.153	-1	0.320
Mechanical Engineering	-0.256	0.161	-1.6	0.112
Gender				
Male	0.153	0.080	1.9	0.057
COURSEDURATION	0.020	0.006	3.26	0.001
ReservationWage2	0.000	0.000	5.55	0.000
Application_8WKS	0.165	0.014	11.7	0.000
jsi				
Medium jsi	-0.018	0.093	-0.2	0.846
High jsi	0.239	0.083	2.88	0.004
Migration_Dummy				
Migrated	0.191	0.079	2.43	0.015
A10_Age	0.025	0.012	2.14	0.032
Examgrade				
Distinction	0.129	0.190	0.68	0.497
Fail	-0.322	0.124	-2.6	0.010
Pass	-0.030	0.085	-0.4	0.728
Refer	-0.200	0.211	-1	0.344
Year_ Completion				
2018	0.291	0.148	1.97	0.049
2019	0.756	0.206	3.66	0.000
_cons	-7.895	0.494	-16	0.000
/gamma	0.019	0.003	6.81	0.000

The model's fit was assessed using the likelihood ratio statistically significant ($\chi^2(7, 1466) = 73.15$, $p = 0.000$). The table 4.49 presents Gompertz coefficients for the field of study and other control factors influencing time to employment. Coefficients for field of study showed statistically non-significant results. For instance, "Agriculture & Environmental Studies" had a positive coefficient of 0.121, but it was not statistically significant ($p = 0.458$). In contrast, "Mechanical Engineering" showed a negative coefficient of -0.256, with a p-value of 0.112, suggesting a non-significant effect. The overall lack of significant results in field of study variables indicated that field of study did not have a strong impact on time to employment.

Gender and other personal characteristics exhibited more notable effects. Additionally, ($p = 0.020$) as were reservation wage and number of job applications ($p < 0.001$) suggesting that these factors had a strong positive influence on the time to employment.

Regarding the impact of job search intensity (jsi) and migration, high JSI had a significant positive coefficient of 0.239 ($p = 0.004$) being associated with shorter job search duration. Migrants also showed a positive effect (0.191, $p = 0.015$), suggesting that geographical mobility may have had an impact on unemployment duration.

Data on exam grades and completion years revealed some significant results. Respondents who entered the job market in 2019 had a significant effect on unemployment duration ($p < 0.001$). Conversely, a failing grade had a negative but statistically significant effect on unemployment duration ($p = 0.010$), highlighting its detrimental impact on the outcome.

4.6.13 Hypothesis Testing

H_O3: The STEM academic field of study has no statistically significant effect on the unemployment duration of graduates of national polytechnics in Kenya.

The study failed to reject this null hypothesis at $\propto = 0.05$ and concluded that STEM academic field of study has no statistically significant effect on the unemployment duration of graduates of national polytechnics in Kenya.

The length of unemployment is influenced by a number of individual and demographic factors in addition to the field of study (Kulik, 2023; Smith & Taylor, 2024; Zhao et al., 2024). It has been demonstrated that a number of variables including age, gender, marital status, immigration status, and education play significant roles in determining the duration of unemployment. These findings suggest that field of study did not significantly affect the time to find employment, a finding consistent with Aguilar et al. (2018). This suggests that, despite the specialization of an individual's academic background, it does not necessarily correlate with a faster or slower transition into the workforce. Additionally, this result aligns with Pedulla and Pager (2019), who found that job search intensity, rather than the specific field of study, slightly increased the probability of finding employment. This implies that active engagement in job searching might be a more critical factor in securing a job than the particular area of academic focus, underscoring the importance of persistence and job market strategies over academic qualifications alone.

The study found that exam grades and years of completion significantly impacted the duration of unemployment, suggesting that academic performance and the time taken to complete one's studies can influence how long individuals remain unemployed after graduation. These findings are consistent with Teichert et al. (2024), who emphasize the importance of both mobility and work experience in determining the length of the transition period from education to employment. However, the effect of these factors on unemployment duration is not straightforward; it varies depending on the type of graduate migration (e.g., domestic vs. international) and previous employment experiences. In some cases, higher exam grades and timely completion of studies may shorten unemployment duration, while in other cases, the type of migration and work history may either exacerbate or alleviate the length of unemployment.

4.7 STEM Academic Program Teaching Resources on Labour Market Outcomes

The fourth objective of the study sought to assess the effect of STEM academic program teaching resources on labour market outcomes for national polytechnic graduates in Kenya. The objective sought to establish the perceptions graduates had about their experience in the STEM field while at the college of study. These perceptions were linked to the employment category outcome using a structural equation modelling. Constructs examined included; training resources, career services, access to institutional academic facilities, and curriculum resources. Perceptions of respondents to these constructs were rated on a likert scale of 1-5.

Indicators of access included; access1(necessary practical tools and materials readily accessible during your TVET program), access2(workshop tools and equipment well-maintained and promptly repaired when needed), and access3(access to specialized workshops (e.g., automotive, electronics, carpentry) relevant to your field of study).

Indicators of career services included; OCS1(how mentorship had been helpful in terms of career guidance, skill development, or networking), OCS2(Participated in any mentorship programs during studies or after graduation), OCS3 (additional resources or support to improve labour market outcomes after graduation and OCS4 (Extent to which practical training and hands-on experience contribute to your employability).

Indicators of Training resources included; TR1(teaching resources align well with industry standards and practices), TR2(satisfied with the workshop facilities (e.g., tools, equipment, space) during your TVET program), TR3(Class size manageable, or did it feel overcrowded), TR4(Rate the quality of teaching resources provided during your program?), and TR5(Use practical resources (e.g., laboratories, software) provided by your program).

Curriculum resources included; Curr1(Curriculum relevant to field of study and future employment?), Curr2(Curriculum adequately prepared for the specific skills and knowledge required by employers in the field of study), Curr3(Opportunities to apply theoretical concepts from the curriculum in practical, real-world scenarios during your studies), Curr4(Curriculum emphasized soft skills alongside technical skills), Curr5(Responsive of curriculum to changes in industry trends and technological advancements).

4.7.1 Partial Least Squares Structural Equation Modelling

PLS-SEM estimates partial model structures by combining principal components analysis with ordinary least squares regressions, integrating both techniques to handle complex models (Hair et al., 2019; Sarstedt et al., 2019). This method is variance-based, as it focuses on maximizing the explained variance of dependent constructs, utilizing total variance for parameter estimation (Hair et al., 2019; Ramayah et al., 2018; Sarstedt et al., 2024). This dual approach allowed PLS-SEM to efficiently model latent constructs, making it suitable for exploratory research and predictive modelling in various fields.

4.7.2 The Structural Model

The study utilized SMART PLS 4 software to examine relationships between key latent variables affecting employment status, the outcome variable, using partial least square structural equation modelling (PLS-SEM). The path model included structural and measurement models, aligning constructs and interrelationships with hypotheses and theory. Exogenous latent variables had outgoing arrows, while endogenous latent variables had incoming arrows.

Hierarchical Component Model (HCM) summarized lower-order components into higher-order constructs, enhancing parsimony and reducing complexity. The main constructs included training resources, curriculum resources, accessibility to teaching resources, career services, and industry linkages that contribute to employment status. Table 4.50 gives a description of the data.

Table 4.50 Descriptive Statistics

Name	Mean	Standard deviation
Access1	2.36	0.734
Access2	2.394	0.747
Access3	2.343	0.797
Curr1	2.579	0.683
Curr2	3.143	1.287
Curr3	2.673	1.39
Curr4	2.19	0.732
Curr5	2.207	0.811
EmployCat	3.771	1.488
OCS1	2.067	0.684
OCS2	2.259	0.984
OCS3	1.605	0.573
OCS4	2.202	0.866
TR1	3.083	1.413
TR2	2.163	0.801
TR3	1.597	0.554
TR4	2.208	0.755
TR5	1.782	0.837
event	0.547	.0129

The table 4.50 presents the mean and standard deviation values for various constructs related to accessibility, curriculum resources, employment category (EmployCat), organizational career services (OCS), and training resources (TR). The mean values indicate the average responses, while the standard deviations reflect the variability of the responses.

The mean values for, Access1 Access2 and Access3 were; 2.36, 2.394 and 2.343, respectively, with standard deviations of 0.734, 0.747 and 0.797. This suggested that respondents had moderate variability. For Curriculum Resources, the mean values range from 2.19 (Curr4) to 3.143 (Curr2), suggesting varying perceptions of different curriculum aspects. The higher standard deviation for Curr3 (1.39) suggests greater variability in responses for that particular item.

Employment Category (EmployCat) has a mean of 3.771 and a standard deviation of 1.488, indicating relatively high ratings for employment outcomes but with considerable variability. Organizational Career Services (OCS) items have mean values ranging from 1.605 (OCS3) to 2.259 (OCS2), with moderate to high variability. Training Resources (TR) items show mean values from 1.597 (TR3) to 3.083 (TR1), with TR1 having the highest variability (standard deviation of 1.413). These results indicate that respondents had diverse opinions on training resources, with some items being rated more consistently than others.

4.7.3 Diagnostics Tests

Factor loading, construct reliability, and validity were critical metrics in the assessment of measurement models within research and data analysis. Factor loading indicated the strength and direction of the relationship between observed variables and their underlying constructs, providing insight into how well variables represented the latent factors. Construct reliability measured the consistency of a construct's ability to accurately reflect its theoretical framework, ensuring that the measurement model was stable and dependable over time. Validity assessed the extent to which a construct accurately captured the intended concept and whether it truly measured what it was supposed to measure. Together, these metrics ensured that research findings were robust, credible, and applicable, underpinning the integrity of the measurement process and the validity of the conclusions drawn. Table 4.51 shows the factor loading, construct reliability and validity.

Table 4.51 Factor Loading, Construct Reliability and Validity

Construct	**Outer loadings**
Access2 <- Accessibility	0.945
Access3 <- Accessibility	0.711
Curr1 <- Curriculum_Resources	0.956
Curr2 <- Curriculum_Resources	0.895
EmployCat <- EmployCat	1.000
OCS2 <- Career_Services	0.943
OCS4 <- Career_Services	0.831
TR2 <- Training Resources	0.935
TR4 <- Training Resources	0.952
event <- Event	1.000

As shown in table 4.51, the factor loadings for these constructs were analysed and indicators whose factor loading was less than 0.7 were removed (Field, 2013). These included Access1, Access2, Curr3, Curr4, Curr5, OCS1, OCS3, TR1, TR3, and TR5. The table shows the factor loading values of the remaining indicators.

4.7.3.2 Construct Reliability and Validity

Table 4:52 Reliability and Validity Tests

Construct	Item	Cronbach's Alpha	(rho_a)	CR (rho_c)	(AVE)
Accessibility	Access1 Access2	0.814	0.887	0.832	0.714
Career Services	Curr1 Curr2	0.871	0.823	0.739	0.537
Curriculum Resources	OCS1 OCS2 OCS3 OCS4	0.863	0.818	0.746	0.527
Training Resources	TR2 TR4	0.869	0.897	0.814	0.624

The Cronbach alpha for exogenous constructs; Accessibility, Career Services, Curriculum Resources, and Training Resources were; 0.814 0.871 0.863, and 0.869, > 0.8 respectively. All the CRs values were higher than the recommended value of 0.700 threshold (Field, 2013). Further, the Average Variance Extraction (AVE) values were all greater than 0.5 for the constructs (Kline, 2016). The data was considered to have met the requirement for further PLS-SEM analysis.

4.7.3.3 Discriminant Validity-Fornell-Larcker Criterion.

The Discriminant Validity Test ensured that constructs in the study were truly distinct and did not measure the same concept. It adopted the Fornell-Larcker Criterion.

Table 4:53 Discriminant Validity Test

Construct	Access	Career Services	Curriculum Resources	Employ Cat	Event	Training Resources
Accessibility	0.845					
Career_Services	0.793	0.733				
Curri_Resources	0.845	0.732	0.726			
EmployCat	-0.234	-0.088	-0.343	1.000		
Event	0.176	0.025	0.289	-0.779	1.00	
Training Resources	0.886	0.846	0.834	-0.193	0.123	0.790

As shown in table 4:53, the values were greater than 0.5, and therefore the data qualified for PLS-SEM analysis.

(a) Heterotrait-Monotrait Ratio (HTMT)

The Heterotrait-Monotrait Ratio (HTMT) measured discriminant validity between constructs as shown in table 4:54

Table 4:54 Heterotrait-Monotrait Ratio (HTMT)

Construct	Accessibility	Career_ Services	Curriculum_ Resources	Employ Cat	Event
Accessibility					
Career Services	0292				
Curriculum Resources	0.174	0.659			
EmployCat	0.301	0.209	0.410		
Event	0.233	0.046	0.369	0.779	
Training Resources	0.332	0.299	0.150	0.204	0.135

The Heterotrain-Monotrait ratio was < .9 for all constructs. The model passed all diagnostic tests for PLS-SEM analysis. Henseler et al. (2015) and Kline, (2016) argue that the Heterotrait-Monotrait (HTMT) ratio of correlations should not have a value exceeding 0.85.

(b) Collinearity Statistics

The Variance Inflation Factor (VIF) was used to detect multicollinearity. It measured how much the variance of the estimated model coefficient increased due to collinearity with other predictors.

Table 4.55 Variance Inflation Factor.

Indicator	**VIF**
Access2	1.244
Access3	1.244
Curr1	2.368
Curr2	3.237
Curr4	1.103
Curr5	1.581
EmployCat	1.000
OCS2	1.679
OCS3	1.080
OCS4	1.588
TR2	2.602
TR4	2.771
TR5	1.106
event	1.000

The results showed the absence of multicollinearity for all the indicators (VIF< 0.5). According to Hair et al. (2019), a Variance Inflation Factor (VIF) value below 5 indicates no significant multicollinearity among the predictor variables in the model.

4.7.3.4 Model Fit

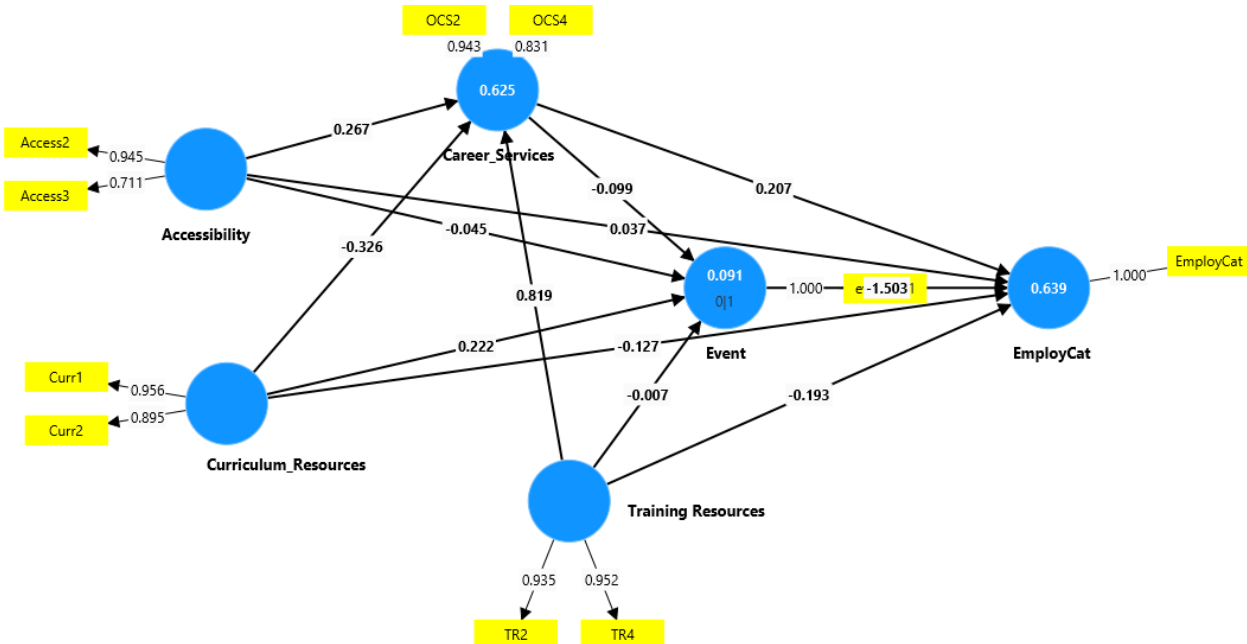

Figure 4.16 Model Estimation Path Coefficient

The model's goodness of fit was computed. The coefficient of determination was 0.639, suggesting that it was well-adjusted and therefore a good fit (Hair et al., 2010).

4.7.3.5 Training Resources on Employment

As shown in figure 4.16 the R-squared value for the model was 0.636 implying that 63.6% of the variance in employment was explained by career services, teaching resources, and curriculum resources. Hair et al. (2019) recommends using the R-squared value, beta, and corresponding t-values via bootstrapping procedure with a resample of 5000 while assessing the PSL-SEM equation.

Table 4:56 Model fit

Test	Saturated Model	Estimated Model
SRMR	0.074	0.074
d_ULS	0.657	0.657
d_G	0.245	0.245
Chi-Square	440.740	440.740
NFI	0.763	0.763

The Saturated and Estimated models exhibit identical fit indices: the Standardized Root Mean Square Residual (SRMR) is 0.074, the Distance-based Upper Bound of the Standardized Residual Sum of Squares (d_ULS) is 0.657, and the Distance-based Goodness-of-Fit Index (d_G) is 0.245. These consistent values suggest there is no discrepancy in model fit between the saturated and estimated models (Sarstedt et al., 2019).

4.7.3.6 Summary Diagnostics

Hair et al., (2019) opines that Composite Reliability (CR) values and average variance extracted (AVE) should exceed exceeded the recommended value of 0.7 and 0.5 respectively. The AVE reflects the overall amount of variance in the indicators accounted for by the latent construct. Both values did not violate the minimum requirement and the discriminant validity values were lower than 0.9 and therefore deemed for analysis. LS-SEM estimates partial model structures by combining principal components analysis with ordinary least squares regressions (Mateos-Aparicio, 2011)

Direct Effect

Direct effect refers to the immediate impact that predictor variables had on the outcome variable without the influence of any mediating variables. These effects were represented by path coefficients, which quantified the strength and direction of the relationship between predictor and outcome variables.

Table 4:57 Relationship among Variables- Path Coefficients

Construct	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
Accessibility -> EmployCat	0.163	0.162	0.059	2.787	0.005
Accessibility -> Event	-0.027	-0.027	0.009	3.002	0.003
Career_Services -> EmployCat	0.150	0.149	0.027	5.638	0.000
Curriculum_Resources -> EmployCat	-0.451	-0.450	0.050	9.039	0.000
Curriculum_Resources -> Event	0.032	0.033	0.009	3.695	0.000
Training Resources -> EmployCat	0.303	0.303	0.047	6.385	0.000
Training Resources -> Event	-0.081	-0.081	0.015	5.465	0.000

The analysis of the relationships between various educational resources and employment outcomes provided insights into how perceptions of these teaching resources influenced employment status by categories. The empirical findings highlight both positive and negative effects, which reflect the complexity of the interactions between educational support mechanisms and employment outcomes.

The positive relationship between perception of accessibility and employment category (EmployCat) with a path coefficient of $\beta = 0.163$ ($t = 2.787$, $p = 0.005$) suggests that greater accessibility to educational resources is associated with better employment outcomes. This finding aligns with research indicating that improved access to educational and career resources can enhance job prospects by providing more opportunities for career development (Schafer, 2020).

Enhanced accessibility to training facilities can facilitate smoother transitions into the job market by removing barriers to information and resources. Conversely, the negative relationship between perception of accessibility and employment status ($\beta = -0.027$, $t = 3.002$, $p = 0.003$) suggests that decreased accessibility might sometimes be associated with lower employment status. This could be due to potential oversupply or saturation in the job market, where increased accessibility might lead to higher competition among graduates, thus impacting the overall employment status negatively (Miller & Rother, 2022). Such dynamics underline the need to balance accessibility with targeted interventions to ensure that increased access translates into tangible employment benefits.

2. Perception of Career Services

Perception of career services demonstrated a significant positive effect on Employment Category (EmployCat) with $\beta = 0.150$ ($t = 5.638$, $p < 0.001$), reinforcing the critical role that career services play in enhancing employment outcomes. This finding is supported by extensive literature that highlights the positive impact of career services on job placement and career progression (Brown & Hesketh, 2019; Hughes & Spalter-Roth, 2020). Effective career services provide crucial support, including job search assistance, resume building, and interview preparation, which significantly contributes to improved employment categories.

3. Perception of Training Resources

Perception of training resources showed a strong positive impact on Employment Category (EmployCat) with $\beta = 0.303$ ($t = 6.385$, $p < 0.001$), indicating that better training resources are associated with higher employment outcomes. This is consistent with findings that emphasize the importance of practical training and skills development in preparing graduates for the job market (Sullivan & Murphy, 2021).

Quality training resources can enhance job readiness and make candidates more competitive, thus improving their employment prospects. However, the negative relationship between perception of training resources and the binary employment status (Event) ($\beta = -0.081$, $t = 5.465$, $p < 0.001$) suggests that extensive training resources might not always lead to improved employment status. This could reflect a mismatch between the training provided and the actual demands of the job market, where an overemphasis on certain types of training may not align with employers' needs (Smith & Zhao, 2022). It underscores the necessity of aligning training programs with industry requirements to maximize their effectiveness.

The significant negative relationship between perception of curriculum resources and Employment Category (EmployCat) with $\beta = -0.451$ ($t = 9.039$, $p < 0.001$) suggests that aspects of the curriculum might have detrimental effects on employment outcomes. This finding is intriguing and may point to potential issues with curriculum design or its relevance to current job market needs. In contrast, the positive relationship between perception of curriculum resources and employment status ($\beta = 0.032$, $t = 3.695$, $p < 0.001$) indicates that while some curriculum elements may benefit employment status, others might not contribute positively to employment categories (Thompson & Carter, 2021).

4.7.3.6 Hypothesis Testing

The fourth objective sought determine the effect of STEM academic program teaching resources on labour market outcomes for national polytechnic graduates in Kenya. The outcome variable was employment category status. The null hypothesis was that

H_04: The STEM academic program teaching resources have no statistically significant effect of on labour market outcomes of graduates of national polytechnics in Kenya.

From the results discussed, the study rejected this null hypothesis at $\propto = 0.05$ and concluded that STEM academic program teaching resources have a statistically significant effect of on labour market outcomes of graduates of national polytechnics in Kenya.

Focus Group Discussion Insights

The Focus Group Discussions (FGD) reported that the introduction of the office of careers in TVET aimed at bridging the gap between labour market information and graduates. This initiative was designed to enhance the flow of information regarding job opportunities and the skills required by potential employers. Interventions are important for improving employment outcomes by ensuring that graduates are well-informed about job market demands and can align their skills accordingly (Johnson & Adams, 2022). The complexity of these findings reflects the multifaceted nature of employment outcomes and the nuanced impact of educational resources. These findings agree with Goldstein & McCulloch (2019) who argue that while educational resources such as accessibility, career services, and training are essential, their effectiveness is contingent upon how well they are integrated into the broader context of labour market needs and individual career planning. Similarly, Additionally, the dynamic interplay between these factors and external economic conditions, such as the impact of COVID-19, further complicates their effects (Wilson & Brown, 2023).

Chen et al. (2022) found that curriculum adjustments negatively impacted employment outcomes when mediated by the binary employment status (Event) participation, aligning with the observed negative indirect effect of curriculum resources on EmployCat. This implied that educational content modifications could influence student engagement in career-related events, ultimately affecting their job prospects. Similarly, Jones & Smith (2022) demonstrated that enhancing accessibility to career services significantly improved employment outcomes, corroborating the positive indirect effect noted between accessibility and EmployCat via career services.

Contrary findings were noted in the literature. For example, Thompson and Carter (2021) reported that changes in curriculum resources did not consistently affect employment outcomes through employment status. Their study found no significant indirect effect of curriculum changes on employment outcomes, suggesting that other factors might mediate this relationship more prominently. Similarly, Lee et al. (2020) found that while accessibility improvements were associated with better career services, these did not always translate into significantly better employment outcomes. They argued that the impact of enhanced accessibility on employment outcomes was moderated by additional variables such as industry-specific factors and local job market conditions.

Additionally, accessibility had a significant indirect effect on the employment status (event) through career services ($\beta = -0.027$, $T = 3.002$, $P = 0.003$), suggesting that improved accessibility indirectly reduced the number or quality of the binary employment status(Event) by enhancing career services. Curriculum resources also indirectly affected EmployCat through Career Services ($\beta = -0.067$, $t = 5.213$, $p = 0.000$), indicating that certain aspects of the curriculum might have negatively impacted employment outcomes by influencing career services.

Training resources did not show a significant indirect effect on EmployCat through employment status ($\beta = 0.011$, $T = 0.245$, $P = 0.806$), implying that the relationship between training resources and employment categorical outcomes was not significantly mediated by employment status. On the contrary, training resources had a significant indirect effect on Employment Category (EmployCat) through career services ($\beta = 0.169$, $t = 7.272$, $p= 0.000$), highlighting career services as a key mediator between training resources and employment categorical outcomes. Additionally, training resources had a significant negative indirect effect on employment status ($\beta = -0.081$, $t = 5.465$, $p = 0.000$), suggesting that training resources might have led to low employment status.

The combined mediation effect of career services and employment status on the relationship between training resources and EmployCat was also significant ($\beta = 0.122$, t

= 5.655, p = 0.000), underscoring the complex interactions among these factors.Smith and Jones (2022), found that enhanced training resources improved employment outcomes primarily through better career services, aligning with the positive indirect effect observed here. However, Brown and Conolly (2021), showed that career services were not always the primary mediator, with industry-specific training and practical experience playing a larger role. This challenges the notion that career services alone mediate the relationship between training resources and employment outcomes.

Additionally, Lee et al. (2018), found that improved training resources often led to more diverse and frequent employment, contradicting the negative effect reported here. This suggests the negative impact on employment status might be context-specific or influenced by other factors.

CHAPTER FIVE

SUMMARY OF FINDINGS, CONCLUSIONS AND RECOMMENDATIONS

`5.1 Introduction

This chapter provides an overview of the study's key findings, aligning them with the objectives, hypotheses, research questions, and analytical approach. It also presents conclusions and recommendations, along with suggestions for future research. The chapter is divided into four sections; a summary of the research findings, conclusions, study recommendations, and suggestions for further research.

5.2 Summary of Research Findings

The purpose of this study was to establish the effect of STEM program characteristics on labour market outcomes of graduates of National Polytechnics in Kenya. As a result, four objectives were established for the study. Accordingly, the summary of findings is presented in four parts, corresponding to these objectives.

5.2.1 Nature of Course on Labour Market Outcomes

The nature of the course while controlling for gender and exam grade affected earnings, with females and those who failed exams generally earning less. Employment in one's field notably increased earnings. Self-employment in a different field of study decreased earnings. Graduates who were employed in a different field of study and migrated from rural to urban areas had better earnings.

The nature of course significantly influenced employment categories. Specifically, employment outcomes were significant for those employed in in their field of study and those employed in a different field of study. However, the nature of study did not significantly affect employment outcomes for self-employment in the field of study, self-employment in a different field, or unemployment. Migration, job search intensity, and longer job search durations positively impacted employment across various categories. Higher academic qualifications and course advancement boosted employment within one's field. A high number of job applications positively affected employment chances.

Graduates of modular programs found employment earlier than those from non-modular programs. Recent job applications improved employment chances slightly, while failing exams significantly reduced the likelihood. Unmarried respondents, particularly females, had a lower likelihood of employment.

5.2.2 Level of STEM Academic Programs on Labor Market Outcomes

Mean earnings increased with higher certification levels up to the diploma level.

In the employment sector, public sector workers had higher mean earnings than private sector workers. Employment in one's field of study combined with certification level positively impacted earnings.

Diploma graduates were more likely to be employed in their field of study compared to artisan certificate. Craft certificate and higher diploma certificate did not have a significant influence on employment in own field of study. Further, respondents with diploma certification were more likely to be self-employed in their field of study compared to being unemployed. Males were more likely to be self-employed in their field of study compared to females. Each additional one-year increase in age increased the likelihood of being self-employed in the field of study.

Additionally, diploma graduates had a higher hazard ratio in comparison to the other levels of certificates. Males had a higher hazard ratio compared to females. Similarly, Male graduates with diplomas had a higher hazard ratio compared to female diploma holders.

There was no statistically significant difference in employment between the public and private sectors of graduates of NPS.

5.2.3 Field of Study on Labour Market Outcomes

Health Sciences, Agriculture & Environmental and Electrical & Electronics Engineering fields of study had higher earnings compared to other fields of study. There exists gender-based earnings differences both within and across fields of study.

The field of study is not determined by one's employment category. However, Migration showed a strong impact across multiple employment categories, underscoring its importance. Academic qualifications and course advancements significantly affected several employment categories, highlighting the role of education and skills in employment. Gender and marital status have variable impact depending on the employment category, suggesting the influence of demographic factors on employment outcomes.

There is variation in median times to employment across different fields, with some fields like health sciences showing a quicker path to employment compared to fields like Hospitality and Electrical Engineering.

5.2.4 Teaching Resources on Employment Outcomes

Improved accessibility to workshops and laboratories was linked to employment in various employment categories. Curriculum resources positively related to employment. Additionally, Accessibility showed a significant indirect effect on employment category via career services indicating that improved accessibility positively impacted employment outcomes through the enhancement of career services. Career services was a key mediator between training resources and employment outcomes.

5.3 Conclusion

The study made the following conclusions.

On the first objective, the study concluded that there was a statistically significant effect of the nature of STEM academic programs on the labour market outcomes of graduates of national polytechnics in Kenya. Modular programs have higher expected earnings compared to non-modular programs. Graduates of modular programs tend to find jobs faster compared to those who pursued non-modular programs.

On the second objective, the study concluded that there was a statistically significant effect of the level of STEM academic programs on labour market outcomes of graduates of national polytechnics in Kenya. Diploma graduates had a higher hazard ratio in comparison to the other levels of certificates. The third objective established that there was a statistically significant effect of the academic field of study on labour market outcomes of graduates of national polytechnics in Kenya. Graduates from fields such as Health Sciences, Agriculture & Environmental Studies, and Electrical & Electronics Engineering tend to have higher earnings compared to those from other disciplines, indicating a strong correlation between field of study and earning potential.

Gender-based earnings disparities are evident within and across these fields, suggesting that demographic factors play a significant role in financial outcomes. While the field of study does not significantly determine employment categories, migration patterns and academic qualifications notably impact employment status, emphasizing the importance of education and skill development.

Additionally, median times to employment vary by field, with Health Sciences graduates typically securing jobs more quickly than those from fields such as Hospitality and Electrical Engineering. This highlights the varying effectiveness of different fields in facilitating prompt entry into the job market.

The fourth objective gave a conclusion that greater accessibility to educational resources is linked to improved employment outcomes, as it enhances job prospects and career development opportunities.

5.4 Recommendations

1. Enhance Modular Nature of Course Programs: TVET institutions should expand and improve modular programs as they are associated with higher expected earnings and faster job placements compared to non-modular programs. Increasing the availability and quality of modular options can better align training with labour market needs.
2. Since diploma level of certification is linked to shorter times to employment and higher earnings, training institutions should implement mechanisms to support academic progression from artisan to craft and diploma levels.
3. Promote Self-Employment: the government and training institutions could develop and support entrepreneurial programs and initiatives that equip graduates from different fields of study with the skills and resources needed for successful self-employment. This includes offering business training, mentorship, and access to funding and startup resources. Additionally, there is need for the national and county governments to create an enabling and conducive environment for the public and private sectors to absorb more youths with STEM qualification.
4. Educational Resources**:** There is need for educational managers and the state department of TVET to improve access to educational resources, as this is associated with better employment outcomes. Training institutions could expand job placement services and career counselling to graduates. This may include personalized support such as resume writing assistance, interview preparation, and networking opportunities.

5.5 Recommendations for Further Research

The study makes the following recommendations for further research.

1. There is need to apply alternative parametric analyses, such as Accelerated Failure Time (AFT) model that could offer deeper insights into the timing and duration of employment outcomes.
2. There is need to conduct longitudinal studies to evaluate how modular programs affect long-term career success, job stability, and career progression compared to traditional programs.
3. Evaluate the components of teaching resources that most effectively enhance employability, such as counselling, networking, mentorship, career talks, job placement, and internship programs.

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Appendix 1: Introductory Letter

Wilberforce Manoah Jahonga

EDE/H/01-70164/2020

P.O BOX 2966, Kakamega-50100

24/02/2023

Dear Sir/Madam,

Mr. Wilberforce Manoah Jahonga is a PhD student at Masinde Muliro University of Science and Technology. He is conducting a tracer study on graduates of National Polytechnic in Kenya with an aim of establishing the labour market outcomes of these graduates. The tracer study is informed by the following concerns; Labour market information on TVET graduate study will help the TVET managers and the ministry of SDVTT to improve on the external efficiency of training by these National Polytechnics. Further, there is need to make informed choices on curriculum development of academic programs that can lead to relevant job opportunities in the market. The study will further provide a base for evaluating career progress and labour market outcomes for future career improvement.

Yours Faithfully,

Wilberforce Manoah Jahonga

Department of Educational Planning and Management

Masinde Muliro University of Science and Technology

P.O. Box 190-50100 | Kakamega

Appendix 2: Interview Schedule for Registrars of National Polytechnics

1. Why are modular programs having shorter time to employment?
2. How does the academic performance of students influence their employment prospects?
3. In your opinion, what strategies do you employ to make sure that graduates of your programs stand out in the job market?
4. What is your comment on the earnings of graduates by field of study?
5. When graduates get employed in a different field of study, what does that portend to your training?
6. How does your training prepare learners for employment in both public and private sector?
7. How does the level of academic programs of your graduates influence the labour market outcomes? Why is there a difference in time to employment for the different levels of qualification (artisan, craft, diploma, higher diploma)?
8. In your opinion, does the negative perception that former graduates have on availability of curriculum resources affect their prospects for employment?

Appendix 3: FGD for Office of Careers Services Coordinators

1. How does the nature of an academic program affect the labour market outcome of STEM graduates in the labour market? Which programs (Modular or Non modular) have better chances for employment outcomes among STEM graduates?
2. How does the level of academic programs of your graduates influence the labour market outcomes? If so, which program has a high labour market outcome? How do graduates with the different qualification (artisan, craft, diploma, higher diploma) fare in the labour market?
3. To what extend does the academic major field of study affect the chances of better labour market outcomes? Does the academic field of study affect labour market outcomes?
4. How has the academic program teaching resources affected the labour market outcomes of your graduates? Could you please explain how the state of workshops and equipment affect the quality of training?
5. What job search support mechanisms does the office/Polytechnics have and how is it implemented?

Appendix 4: Telephone Interview for Graduates of National Polytechnics

Name of fieldwork data collector		To be entered manually
Mobile No. of data collector		
Date:		

#	Introduction and screening questions	Option	Comment
A	Hello, my name is ________ I am calling you on behalf of Mr. Wilberforce Manoah Jahonga, a PHD student at Masinde Muliro University of Science and Technology . (You are allowed to greet the person and introduce yourself)		
1	Can I confirm that I am speaking to__________________ (a former student of (_______________) name the national polytechnic?	1. Yes 2. No	If No, stop thank the him/her and start your next interview.
B	Mr. Jahonga is collecting information from past trainees who pursued STEM programs from 11 National Polytechnics in Kenya who were enrolled in the year 2016. This study will help to determine the labour market outcomes of former students who studied in these institutions. Further, consider these as part of a PHD requirement by Masinde Muliro University of Science and Technology to collect relevant data that can be used to address this research goal.		Continue to Q1
1	Are you willing to participate in the survey? Your participation in this survey is voluntary and your responses will be kept confidential. The survey is expected to take less than 20 minutes.	1. Yes 2. No	If yes, continue to Q1 If ":no"" thank the person and end the call

SECTION 2: BACKGROUND INFORMATION			
#	Background Information Questions	Option	Comment
	I will start by asking you a few questions on you and your training		
	Where did you study?	Eldoret National Polytechnic Kabete National Polytechnic Kenya Coast National Polytechnic Kisii National Polytechnic Kisumu National Polytechnic Kitale National Polytechnic Kenya School of TVET Meru National Polytechnic North Eastern National Polytechnic Nyeri National Polytechnic Sigalagala National Polytechnic	Have a drop-down menu of the names of the TVET. The enumerator simply selects
	What is your gender? You are free to decline to answer Read out the options 1- 2)	1. Female 2. Male	Drop down menu
	How old are you in years	Insert figure in years	
	In which county were you born? (Do not read out	Baringo County Bomet County Bungoma County Busia County Elgeyo Marakwet Embu County	Have a drop-down menu of the names of the counties.

SECTION 2: BACKGROUND INFORMATION			
#	Background Information Questions	Option	Comment
	the options)	Garissa County Homabay County Isiolo County Kajiado County Kakamega County Kericho County Kiambu County Kilifi County Kirinyaga County Kisii County Kisumu County Kitui County Kwale County Laikipia County Lamu County Machakos County Makueni County Mandera County Marsabit County Meru County Migori County Mombasa County Maranga County Nairobi County Nakuru County Nandi County Narok County Nyamira County Nyandarua County Nyeri County Samburu County Siaya County Taita Taveta Tana River County Tharaka-Nithi Transzoia County Turkana County Uasin Gishu Vihiga County Wajir County	The enumerator simply selects

SECTION 2: BACKGROUND INFORMATION			
#	Background Information Questions	Option	Comment
		West Pokot County	
	In which county do you live now? (Do not read out the options)	Baringo County Bomet County Bungoma County Busia County Elgeyo Marakwet Embu County Garissa County Homabay County Isiolo County Kajiado County Kakamega County Kericho County Kiambu County Kilifi County Kirinyaga County Kisii County Kisumu County Kitui County Kwale County Laikipia County Lamu County Machakos County Makueni County Mandera County Marsabit County Meru County Migori County Mombasa County Muranga County Nairobi County Nakuru County Nandi County Narok County Nyamira County Nyandarua County Nyeri County Samburu County Siaya County Taita Taveta	Have a drop-down menu of the names of the counties. The enumerator simply selects

SECTION 2: BACKGROUND INFORMATION			
#	Background Information Questions	Option	Comment
		Tana River County Tharaka-Nithi Transzoia County Turkana County Uasin Gishu Vihiga County Wajir County West Pokot County	
	Where do you live? (Read out the options)	Uban Peri-urban Rural	If option 1 is chosen, continue to Q11 If option 2 and 3 skip to Q12
	Is employment the reason where you live currently?	Yes NO	
	What is the type of your residential area	Formal settlement Informal settlement	If option 1 is chosen, continue to Q11 If option 3, 4, and 5 skip to Q12
	What is your marital status? (Read out the options)	1. Married 2. Not Married	If option 1, continue to Q11 If option 2, 5 skip to Q13
.	Does your partner currently	1. Yes 2. No	

SECTION 2: BACKGROUND INFORMATION			
#	Background Information Questions	Option	Comment
	have a job?		
.	Do you have any children?	1. Yes 2. No	If option 1 yes is chosen, continue to Q13 If option 2 no is chosen skip to Q14
.	How many children do you have	Open-ended	Here insert a number
.	Who sponsored your education? (Read out options 1 to 7)	1. Purely Self sponsored 2. Self-sponsored with HELB loan 3. Self-sponsored with HELB loan and government capitation 4. National Youth Service 5. Non-Governmental Organization 6. Religious Organization 7. County government 8. Others(specify)	Drop down menu/selection
.	What was your field of study? (tick one)	1. Agriculture & Environmental Studies 2. Applied Sciences 3. Building & Civil Engineering 4. Electrical & Electronics engineering 5. Health Sciences 6. Information & communication Technology & Informatics 7. Institutional Management, Clothing/Fashon/ Hair Dessing 8. Mechanical & Automotive Engineering	Drop down menu/selection
.	What is the name of the course you	Close-ended	Link course to field of study. This

SECTION 2: BACKGROUND INFORMATION			
#	Background Information Questions	Option	Comment
	studied for at the National Polytechnic?		is very important to avoid unnecessary data cleaning exercise
.	Was is a modular or Non Modular program?	1. Modular 2. Non-Modular	
.	What was the level of your program at the time you started your course at the National Polytechnic?	1. Artisan 2. Craft 3. Diploma 4. Higher Diploma	
.	When did you start your course? (Give the respondent time to recall if possible exact month and year)	MM/YYYY	
.	What is the highest level of qualificati	1. Artisan 2. Craft 3. Diploma 4. Higher Diploma	Have a drop-down menu of the level of

SECTION 2: BACKGROUND INFORMATION			
#	Background Information Questions	Option	Comment
	on since you left/completed your course at the National Polytechnic?	5. Degree	courses. The enumerator simply selects
.	Did you advance your course?	1. Yes 2. No	If option 2 "No", Skip to Q20
.	To what level did you advance your course?	1. Artisan to Craft 2. Craft to Diploma 3. Craft to Diploma to Higher diploma 4. Diploma to Higher Diploma	Have a drop-down menu of the level of courses. The enumerator simply selects
.	Did you complete your studies at your college?	1. Yes 2. No	If option 1 Yes is chosen, continue to Q20 If "No" is chosen skip to Q22
.	When did you finish your course?	MM/YYYY	
.	How many qualifications did you acquire at your	1. Artisan Certificate only 2. Craft Certificate only 3. Diploma Certificate only 4. Higher Diploma Certificate only 5. Artisan and Craft Certificates only 6. Artisan, Craft and Diploma Certificates	Have a drop-down menu of the level of courses. Some

SECTION 2: BACKGROUND INFORMATION			
#	Background Information Questions	Option	Comment
	National Polytechnic?	7. Craft and Diploma Certificates only 8. Craft, Diploma and Higher Diploma 9. Diploma and Higher Diploma Certificates	respondents may have advanced from one level to another. The enumerator simply selects
.	Did you go through an industrial attachment program during the course training?	1. Yes 2. No	If No, skip to section 3
.	How many sessions of Industrial attachment program did you attend?	State figure	

SECTION 3: EMPLOYMENT STATUS PRIOR TO TRAINING			
#	Employment Status Prior To Training Questions	Option	Comment
	I am now going to ask you about your employment situation before you started your course.		
.	What were you doing before you enrolled for the course at the national polytechnic? (Read out options 1 to 6)	1. Employed 2. Unemployed 3. Self-employed/freelance work 4. Internship / Voluntary	If options 1 is chosen to skip to Q27 If option 2 is chosen skip to Q35 If option 3 is chosen skip to Q27 and exclude

SECTION 3: EMPLOYMENT STATUS PRIOR TO TRAINING			
#	Employment Status Prior To Training Questions	Option	Comment
		5. Domestic or home help 6. = other	28, 29 and 30. If option 4 is chosen skip to Q28 If option 5 is chosen continue to Q 27 If option 6 is chosen skip to Q33 If option 7 is chosen skip to Q33
.	Was this internship/voluntary work paid or unpaid?	1. Paid 2. Unpaid	If 1. paid option chosen continue to Q27 If unpaid option chosen, go to Q 27 to Q33 but Exclude Q29
.	Before the training at the national polytechnic, what was your job or activity?	Open-ended	
.	Before the training at the national polytechnic, in which sector, were you working? (Read out options 1-4 only)	1. Public sector 2. Parastatal 3. Private sector 4. Civil society and NGO 5. Other 6. 6.Don't remember	
.	Before the training at the national polytechnic what type of contract did you have. (Read out options 1-5 only)	1. Permanent contract 2. Fixed-term contract 3. Permanent oral agreement 4. Fixed-term oral agreement 5. No contract of any form 6. Other, please specify	

SECTION 3: EMPLOYMENT STATUS PRIOR TO TRAINING			
#	Employment Status Prior To Training Questions	Option	Comment
.	Before the training at the national polytechnic, what was your job category (Read out options 1-6)	1. Qualified worker 2. Semi-qualified worker 3. Casual Labourer 4. Intern/ Volunteer 5. Other. 6. Don't remember	
.	In this work, was it full time or part time?	1. Time/day or week 2. Don't remember	
.	Did you work on the weekend? (Read out options	1. Yes, one day 2. Yes, two days 3. No	
.	On average, how much do you estimate your monthly income was? (state figure)	Kenya KSh ______________________	If other, the respondent does not know exactly but can estimate income by number of harvest or any other amount write down exactly what they say.
.	Was this job or activity related to the course you pursued at the National Polytechnic?	1. Yes 2. No	

SECTION 4: CURRENT EMPLOYMENT STATUS			
#	Current Employment Situation Questions	Options	Comment
	I am now going to ask you some questions about your current employment status		

.	What is your current employment status? (Read out options) (Can select one option only)	1. Employed in the area of study 2. Employed in another area of study 3. Self Employed in the area of study 4. Self-employed in another area of study 5. Unemployed 6. Student	Drop down menu If option 1-4 (employed) is chosen skip to Q56 If option 5 and 6 (self unemployed) is chosen continue to Q87 If option 7(Unemployed) is chosen skip to Q38 If option 8 (Internship/Voluntary work) is chosen continue to Q34 If option 9 (student) is chosen skip to Q101

SECTION 4A: CURRENT EMPLOYMENT STATUS - <u>UNEMPLOYED</u>			
#	Unemployed Questions	Options	Comment
.	Since when have you been unemployed after completing your study at the national polytechnic?	1. MM/ YYYY	While we are asking for months and years respondents may not know these, If part or all of the date is missing use 99 or 9999. For example /99/999 or 99/2017.
.	Are you currently looking for a job	1. Yes 2. No	If yes continue to Q 40 If no skip to Q43
.	What type of work are you looking for regarding the type of contract (Read out options)	1. Permanent contract 2. Fixed-term contract 3. No contract 4. Self-employed 5. No preference	

SECTION 4A: CURRENT EMPLOYMENT STATUS - UNEMPLOYED			
#	Unemployed Questions	Options	Comment
.	What type of work are you looking for in relation to your training (Read out options)	1. Corresponding to your training 2. Not corresponding to your training 3. No preference	
.	Did you have some of the following problems when looking for work:		
39.1	Lack of work experience	1. Yes 2. No	
39.2	Don't know how to find a job	1. Yes 2. No	
39.3	No suitable jobs in the area I live in	1. Yes 2. No	
39.4	Salary offered too low	1. Yes 2. No	
39.5	My course has never helped me find a job	1. Yes 2. No	
39.6	My skills are not needed in the job market	1. Yes 2. No	
39.7	No personal connections to help find a job	1. Yes 2. No	
39.8	Did you have any other problems when looking for work?	1. Yes 2. No	
39.9	If yes, please specify	Open ended	
.	Have you ever been employed or self-employed since graduating from the national polytechnic? (Choose one option only) (Read out options1 to 4)	1. Yes employed 2. Yes self-employed 3. No 4. Don't remember	If yes, employed, continue to Q46 If yes, self-employed skip to Q 48 If no skip to Q117 If I don't remember skip to Q87
.	How many jobs have you held so far?	Insert figure	

SECTION 4A: CURRENT EMPLOYMENT STATUS - UNEMPLOYED			
#	Unemployed Questions	Options	Comment
.	What was your latest job or activity before you became unemployed?	Related to my field of study Not related to my field of study	
.	When did you start working after your graduation/completing your course?	MM/YYYY	
.	When did you stop working in that job?	MM/YYYY	While we are asking for months and years respondents may not know these, If part or all of the date is missing use 99 or 9999. For example /99/999 or 99/2017.
.	Why did you leave your last job? (Do not read out options)	Personnel restructuring Enterprise closed down Privatization/Restructuring Fired Contract expiry Due to low salary Due to further training Family constraints/responsibilities You don't remember Other	If options 1-9, skip to Q87 If option 10 (other), skip to Q50.1
.	If other, please specify	Open-ended	Skip to Q117

SECTION 4B: CURRENT EMPLOYMENT STATUS - EMPLOYED			
#	Employed Questions	Option	Comment
52.	What is your current job or activity?	Open-ended	
53.	When did you start working in your current job?	MM/YYYY	While we are asking for months and years respondents may not know these, if part or all of the date is

SECTION 4B: CURRENT EMPLOYMENT STATUS - <u>EMPLOYED</u>			
#	Employed Questions	Option	Comment
			missing use 99 or 9999. For example, 99/999 or 99/2017.
54.	Is this job your first job since you graduated/completed your studies at your national polytechnic?	1. Yes 2. No	If yes go to Q61 If no continue to Q59
55.	Can you remember when you started your first job after completing your study?	MM/YYYY	While we are asking for months and years respondents may not know these, if part or all of the date is missing use 99 or 9999. For example 99/999 or 99/2017
56.	Can you remember when you left this first job?	MM/YYYY	While we are asking for months and years respondents may not know these, if part or all of the date is missing use 99 or 9999. For example, 99/999 or 99/2017
57.	In which sector are you currently working? (Read out options)	1. Public sector 2.Private sector 3. Other	If option1 is chosen skip to Q56
58.	If other, please specify	Open-ended	
59.	What type of private sector are you working in?	1.Formal 2.Informal	
60.	Can you confirm if this job or activity is in your field of study?	1. Yes 2. No	if yes continue to Q63 If no skip to Q65
61.	If other, please specify	Open ended	
62.	How did you get this job? (Read out options 1-6 only)	1. Due to an internship 2. Due to a spontaneous application 3. Due to your connections 4. Through an employment agency 5. After applying for a vacancy 6. After passing the public servant test 7. Refuse to answer 8. Don't remember 9. On line job matching platform 10. Other	
63.	If other, please specify	Open-ended	

SECTION 4B: CURRENT EMPLOYMENT STATUS - <u>EMPLOYED</u>			
#	Employed Questions	Option	Comment
64.	What is your contract type? (Read out options 1-5 only)	Public Private	
65.	If other, please specify	Open-ended	
66.	On average, how much do you estimate your monthly income is? For people in the formal sector ask for their net income (Read out options)	Kenya KSh ______________________	
67.	If you receive in-kind payments or benefits, what are they? (Select all which apply) (Read out options)	1. No in kind payment 2. Farm products (meat, milk, etc.) 3.Travel allowance 4. Vehicle allowance 5. Mobile phone credit or allowance 6. Free housing/ housing allowance 7. Medical aid 8. Pension/retirement fund 9. Other (specify)	If other specify
68.	Based on your experience in your work, does your current work match to your training at the national polytechnic? (Do not read out options.)	1. Yes 2. No 3. Somewhat 4. I don't know	If 1 is chosen, skip to Q78 If 2 is chosen, continue to Q77 If 3, is chosen continue to Q77 If 4, is chosen continue to Q77
69.	If your job does not match your course of study, why did you choose this job? (Read out options)	1. You did not want to work in your course of study 2. You could not find a job using our course of study 3. You get paid more 4. You wanted more job security 5. Other, specify	
70.	Have you ever run your own business or activity?	1. Yes 2. No	If yes, continue to Q80 If no, skip to Q85
71.	What was your business or activity?	Open-ended	
72.	Can you reconfirm if this business or activity was in your field of study?	1. Yes 2. No	if yes continue to Q82 If no skip to Q83
73.	Do you still have the business?	1. Yes 2. No	If yes continue to Q84 If no Skip to Q85

SECTION 4B: CURRENT EMPLOYMENT STATUS - <u>EMPLOYED</u>			
#	Employed Questions	Option	Comment
74.	How much do you earn in a month from this business	Open-ended	Or how much profit did you generate in the business
75.	Do you do any other paid work besides your main work or your business	1. Yes 2. No	If yes continue to Q85.1 If no continue to Q117
76.	Please specify what	Open ended	
77.	How much do you earn from this	1. Open ended 2. Refuse to answer	Skip to Q117

SECTION 4C: CURRENT EMPLOYMENT STATUS - SELF EMPLOYED			
#	Self Employed Questions	Option	Comment
8.	What is your business or activity?	Open-ended	
9.	What was the reason for you to become self-employed? (Select all which apply) (Read out options)	• You could not find paid work • You could not find work in the field you were trained in • Paid work is badly paid • You prefer to work more flexibly • You are entrepreneurial • You like to be your own boss • You are still looking for paid work • Other (specify)	If other please specify
0.	Can you please reconfirm if this business or activity is in your field of study or related sector?	1. Yes 2. No	if yes continue to Q90 If no skip to Q91
1.	Can you remember what was the date you set up your own business or activity?	MM/YYYY	While we are asking for months and years respondents may not know these, if part or all of the date is missing use 99 or 9999. For example, 99/999 or 99/2017.
2.	On average, how much do you estimate your monthly income is? (Read out options 1-5 only)	Kenya KSh -----------------------------	

SECTION 4C: CURRENT EMPLOYMENT STATUS - SELF EMPLOYED			
#	Self Employed Questions	Option	Comment
	If respondent, does not know exactly but can estimate income by number of harvest or any other amount, select other and write down exactly what they say.		
3.	Although you are currently self-employed, have you ever been employed somewhere since finishing your study?	1. Yes 2. No	If yes, continue to Q94 If no, skip to Q96
4.	Can you remember when you started working in your first job after finishing your course?	MM/YYYY	While we are asking for months and years respondents may not know these, if part or all of the date is missing use 99 or 9999. For example, 99/999 or 99/2017
5.	Can you remember when you stopped working in your first job after finishing the NPs course	MM/YYYY	While we are asking for months and years respondents may not know these, if part or all the date is missing use 99 or 9999. For example, 99/999 or 99/2017
6.	Would you leave your business or activity if you found formal or full-time employment (Do not read out options)	1. Yes 2. No 3. Don't know	

SECTION 4D: CURRENTLY IN TRAINING			
#	Currently In Training	Option	Comment
37.	Why did you decide to start/study this course (unit of learning/module) (Select all which apply) (Read out options)	1. You could not find work 2. To get additional qualifications 3. To get additional specific skills 4. To make up for your missing skills or training 5. Improve your situation in the job market 6. Increase your income 7. To get new skills in order to set up your own business 8. Other	If other, please specify

SECTION 4D: CURRENTLY IN TRAINING			
#	Currently In Training	Option	Comment
88.	Can you remember when you started the course?	MM/YYYY	While we are asking for months and years respondents may not know these, If part or all of the date is missing use 99 or 9999. For example, 99/999 or 99/2017
89.	Although you are currently in training have you ever been employed or self-employed since graduating from the NPS institution (Read out options) (Select one option only)	1. Yes, occasional jobs (just to earn money) 2. Yes employed 3. Yes self-employed 4. No	If yes, occasional job continue to Q117 If yes, employed, continue to Q 107 If yes, self-employed skip to Q113 If no skip to Q117
90.	What was your job or activity?	Open ended	
91.	When did you start working?	MM/YYYY	
92.	Can you also please reconfirm what specific activities the work mostly focused on? (Select all which apply) (Read out options)	1. Input provision 2. Production 3. Harvesting 4. Processing 5. Commercialization 6. Other, specify	Respondent can provide as many as they want If the enumerator has any doubt where to fit an answer , put it under other

SECTION 5: RETROSPECTIVE EVALUATION OF TRAINING AND TEACHING RESOURCES						
Access: Kindly rate your perception about the following on a scale of 1-5						
		1	2	3	4	5
Access	Access1-necessary practical tools and materials readily accessible during your TVET program					
	Access2-workshop tools and equipment well-maintained and promptly repaired when needed					
	Access3-access to specialized workshops (e.g., automotive, electronics, carpentry) relevant to your field of study					
career services	OCS1-how mentorship had been helpful in terms of career guidance, skill development, or networking?					
	OCS2-Participated in any mentorship programs during studies or after graduation?					
	OCS3- additional resources or support to improve labour market outcomes after graduation?					
	and OCS4 (Extent to which practical training and hands-on experience contribute to your employability?).					
Teaching Resources	TR1(teaching resources align well with industry standards and practices?)					
	TR2(satisfied with the workshop facilities (e.g., tools, equipment, space) during your TVET program?),					
	TR3(Class size manageable, or did it feel overcrowded?),					
	TR4(Rate the quality of teaching resources provided during your program?),					
	TR5(Use practical resources (e.g., laboratories, software) provided by your program?).					
Curriculum Resources	Curr1(Curriculum relevant to field of study and future employment?),					
	Curr2(Curriculum adequately prepared for the specific skills and knowledge required by employers in the field of study?)					
	Curr3(Opportunities to apply theoretical concepts from the curriculum in practical, real-world scenarios during your studies?),					

	Curr4(Curriculum emphasized soft skills alongside technical skills?)					
	Curr5(Responsive of curriculum to changes in industry trends and technological advancements?).					

THANK RESPONDENT, RECORD END TIME AND CLOSE INTERVIEW

Appendix 5: Research Permit

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR SCIENCE, TECHNOLOGY & INNOVATION

Ref No: **100280**

Date of Issue: **05/April/2023**

RESEARCH LICENSE

This is to Certify that Mr.. Wilberforce Manoah Jahonga of Masinde Muliro University of Science and Technology, has been licensed to conduct research as per the provision of the Science, Technology and Innovation Act, 2013 (Rev.2014) in Garissa, Kakamega, Kiambu, Kisii, Kisumu, Meru, Mombasa, Nairobi, Nyeri, Transnzoia, Uasin-Gishu on the topic: STEM Program Characteristics and Labour Market Outcomes of Graduates of National Polytechnics In Kenya for the period ending : 05/April/2024.

License No: **NACOSTI/P/23/25043**

100280

Applicant Identification Number

Director General
NATIONAL COMMISSION FOR SCIENCE, TECHNOLOGY & INNOVATION

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See overleaf for conditions

Mwenzwa & Misati (2014) posits that the social pillar focuses on education and training, youth, gender highlighting its crucial role in fostering social development and addressing inequality. Integrating STEM into these policy frameworks is essential in sustainable economic growth and youth employment. The GoK outlined the Big 4 Agenda; food security, affordable housing, manufacturing, and affordable healthcare for all (GoK, 2013). The aim was to create jobs that would enable Kenyans to meet their basic needs. TVET in South Africa is has the potential of contributing to skills training at the intermediary skill level and being a catalyst to growing the country's economy while providing better employment opportunities for the youth (Honorati et al., 2024). Powell (2013), adds that skills development needs to move toward a more theoretical direction foster the development of a strong research community. There is therefore a need to prioritize the need for a skills system that responds to market requirements and employer needs (Bhorat et al., 2013)