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FROM ACADEMIA TO CAREERS: A COMPARATIVE STUDY OF COX AND PARAMETRIC AFT SURVIVAL MODELS ON ARUSHA TECHNICAL COLLEGE'S GRADUATES CLASS OF 2022

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ABSTRACT

The purpose of this study is to determine what factors affect the time it takes Arusha Technical College graduates to land their first job following graduation. The study examines the length of unemployment for 568 graduates from 15 academic programs using information from a tracer survey carried out in 2022. The effect of academic programs, job search tactics, and demographic traits such as gender and age on graduates' employment outcomes is investigated through the use of survival analysis techniques, such as the Cox proportional hazards model and the Kaplan-Meier estimator. The results show that the median time to start employment is roughly 10 months, with differences seen depending on the company category, gender, age group, academic degree, and job search tactics. Moreover, it is observed that male graduates are more likely than female graduates to secure employment before their peers, and that some academic programs have higher rates of job placement. The government sector is the most advantageous for early employment, followed by private and self-employment. Furthermore, graduates who use internet-based job search strategies also find employment more quickly than graduates who use other methods. Consequently, age, academic program, and job search strategy all have a substantial impact on graduates' employment outcomes, which has implications for career development initiatives and industry-academia partnerships.

KEYWORDS: Graduate employment, Survival analysis, Cox proportional hazards model, Job search strategies, Gender disparities.

INTRODUCTION

Securing employment immediately after graduation is a significant difficulty that is shared by educational institutions worldwide. As graduates transition to the workplace, their expectations meets the markets' demand. Among the 768 Arusha Technical College graduates in 2022, 568 of whom participated in a complete tracer study, the post-graduation period showed a narrative of how taught skills corresponded with the changing needs of the Tanzanian labor market.

The current discussion on the issues of graduate employment highlights the tension between educational institutions' output and the changing labor market needs. As the global economy develops in terms of technology, industry demands, and market dynamics, graduates frequently find themselves in unfamiliar territory while looking for instant employment (Wehman, 2013). The disparity between what graduates deliver and what businesses desire might lead to extended wait times for that critical first job.

Unemployment has far reaching societal ramifications that go beyond the individual (Ahmed et al., 2012). High levels of graduate unemployment can hinder economic growth, limit individual career paths, and result in a mismatch between skills and industry demands. In Tanzania, where Arusha Technical College plays an important role in creating technical experts, understanding the factors influencing the waiting period for first employment is critical for both institutional improvement and national development.

LITERATURE REVIEW

The obstacles that graduates confront as they transition from university to employment have been extensively researched around the world. This literature review seeks to give a complete overview of the factors impacting graduate employability, waiting times, and job market dynamics. Drawing on research conducted in other nations allows for a more general picture of the employment landscape at Arusha Technical College.

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The choice of specific locations for this study is motivated by a strategic desire to gain insights from varied worldwide experiences, resulting in a comprehensive framework for understanding the difficulties and dynamics of graduate employability.

A major shift that resulted in a rise in the number of university graduates was the 1999 expansion of China's higher education system (Shi & Xing, 2010). However, with so many graduates joining the workforce, it has created a situation where a sizable percentage of them stay unemployed or underemployed for a long periods of time (Jun, 2017). The quest of high paying jobs in pleasant working settings becomes an important part of career advancement. College status, professional sectors, and personality and economic factors have all been cited as impacting job searches and starting earnings (Kong, 2013; Kong & Jiang, 2011).

Particular attention has been paid in Chinese studies to the effects of individual characteristics on graduate employment. Important factors that come into consideration include gender, and the reputation of the college. It has been discovered that a college's reputation has a major impact on graduates' job searches, with research universities and specific professional specialties controlling the initial labor market. Studies on the subject differ in their conclusions about the impact of gender; some contend that women graduate students enter the workforce earlier than men, while others point to other patterns, such as the difficulty women graduates face in getting employment.

In Ethiopia, the issues of graduate employment are in line with the global narrative. Despite an increase in employment options, thousands of new graduates face problems in their rapid transition from graduation to employment (Alemu & Yismaw, 2022). According to the 2011 World Bank database, the general unemployment rate was 20.5% in 2009. This emphasizes the necessity to investigate the factors that contribute to long wait times and unemployment(Adelo Wobse et al., 2022; Merie et al., 2022). Regarding the factors influencing waiting times for first job, research done in Ethiopia has produced conflicting and ambiguous results. Studies by (Getie Ayaneh et al., 2020) reported a median waiting time of 15 months, while (Fenta et al., 2019) found graduates waiting slightly over five months. Determinants such as the cumulative grade point average (CGPA) have been explored, with varied results (Getie Ayaneh et al., 2020) . Given the lack of definitive results from these empirical studies, a more thorough and context-specific analysis of Ethiopian graduates' employability is imperative.

In addition, research conducted in the United Kingdom has investigated how graduates' job search results are affected by the prestige of their education. According to (Yibeltal Yizengaw, 2018) study, graduates' job searches are greatly influenced by a college's reputation.

The results demonstrate how competitive the job market is, with graduates from recognized universities having an advantage in landing a job. This focus on collegiate reputation is consistent with the experiences of the Chinese, highlighting the institutional prestige's universal value in the job market (Kong, 2013).

In Norway, gender differences have been investigated by (Nilsen & Bratberg, 1998) about graduates' entry into the labor market. According to (Nilsen & Bratberg, 1998) model, Norwegian women graduates typically join the workforce before their male counterparts. The study does not specifically address the transition from education to the workforce, but the gender dynamics in labor market entry that are noted can be seen as a part of the larger picture of employability (Ahmed et al., 2012). Although not explicitly addressing the academic- to-professional transition, their research offers insightful information about variables influencing graduates' first job entry. Our knowledge of how gender-related factors affect graduates' timing of entering the workforce is enriched by the Norwegian findings. Although this insight does not immediately address the difficulties associated with the academic-to-career transition, it does offer context for the complex nature of employability considerations. (Ama, 2008) investigated waiting times for initial employment and the factors influencing these durations in a study done in Botswana. The results, which show an average waiting period of 4.6 months, advance our knowledge of graduate waiting periods. The disparities in waiting periods observed between areas highlight the necessity of region-specific measures to address the particular difficulties graduates confront.

Moreover, the role that the cumulative grade point average (CGPA) plays in graduates' employment has been studied in Rwanda. The CGPA of graduates has little bearing on their employability, according to a study by (Niragire & Nshimiyiryo, 2017) on determinants of increasing length of first unemployment among first degree holders in Rwanda: a logistic regression analysis. This result is in contrast to research from other sources, including (Mehmetaj & Zulfiu Alili, 2021)and (Ndagijimana et al., 2018), which came to the opposite conclusion. The contradictory results show the need for assessments tailored to the particular situation and the variety of factors affecting employability.

From this point forward, comprehending patterns and disparate results in graduate employability requires a global perspective. The global recession, widespread access to higher education, and growing demand for education have all led to a competitive labor market on a global scale. Graduates' experiences across a range of geographic locations highlight how employability issues are constantly changing and how crucial it is to address them with context specific strategies.

METHODOLOGY

This study employed a comparative research design with a specific focus on the survival analysis of waiting times to first employment for graduates in different regions. The comparative approach allows for a more exploration of how gender, age group, program studied, and employment search strategies contribute to the "survival" in the labor market of graduates.

Source of Data and Data Collection Procedures

The primary data for this study were derived from the 2022 tracer survey conducted at Arusha Technical College. The survey targeted graduates from the academic year 2021/2022, providing a comprehensive overview of their employability outcomes. The total number of potential respondents was 768 graduates, and the study successfully collected responses from 568 individuals, representing an impressive 74% response rate. To ensure comprehensive data collection, a structured questionnaire was employed. The questionnaire covered various aspects, including demographic information, employment status, duration taken to secure employment, and the perceived relevance of the training received at Arusha Technical College. Google Forms served as a convenient and efficient platform for collecting responses from the graduates. An email invitation was extended to all graduates, providing them with access to the online survey. This method facilitated broader participation, allowing graduates to respond at their convenience

Recognizing the importance of personal interaction as suggested by (Van der Heijden et al., 2009), a team of Arusha Technical College staff visited graduates physically at their current locations. This approach ensured inclusivity, especially for those who might face challenges with online access. The team administered the structured questionnaire in person, capturing responses on-site. Collected data, in both online and physical formats, were transferred to the Statistical Package for the Social Sciences (SPSS) and Stata, for comprehensive analysis.

Variables

The study encompasses several variables to comprehensively explore the transition from graduation to first employment. The primary outcome variable is the duration, in months, from graduation to first employment. Demographic factors, including age and gender, are examined to understand their influence on employment duration, drawing insights from existing literatures such as (Kuhn & Skuterud, 2004). Additionally, the choice of academic program is examined as a pivotal variable, recognizing its significance in influencing employability outcomes. The study also scrutinizes job searching methods, encompassing public advertisement, internet searches, and networking, drawing on insights from works by (Klein & Moeschberger, 1997).

Statistical Analyses

The statistical analysis employed in this study included various approaches to offer a comprehensive understanding of the factors influencing the waiting time to first employment for graduates of Arusha Technical College. Descriptive statistics were used to report the base characteristics of the study population. The unemployment curve was estimated using the Kaplan-Meier method, this non-parametric approach allowed for the calculation of the cumulative probability of graduates remaining unemployed over time. It is particularly effective in capturing the distribution of waiting times until the occurrence of the event of interest, which, in this study, is obtaining the first employment. For the assessment of associations, survival regression models were applied. The Cox Proportional Hazards (Cox PH) model was employed to examine how hazard rates change over time based on covariates.

Additionally, the Parametric Accelerated Failure Time (AFT) model was used to assess the effect of covariates on the time scale directly. This model provided insights into how changes in independent variables accelerated or decelerated the time to the event of interest..

Descriptive Statistics

In the sample of 568 graduates, it was found that 316 (55.63%) graduates were employed at the time of the study. As shown in Table 1, the proportion of employment for females differs significantly compared to males. Out of the 120 female graduates, 57 (47.50%) were employed at the time of the study. In contrast, among the 448 male graduates, 259 (57.81%) were employed. In terms of job search methods, graduates employed various strategies. The majority, 126 graduates (49.41%), used personal connections such as relatives, friends, and colleagues to secure employment, underscoring the significance of net- working in the job search process. Additionally, 101 graduates (39.53%) relied on online resources, with the internet serving as a key platform for job hunting.

Survival Data Analysis

Survival analysis, as outlined by (Kaplan & Meier, 1958; Orbe et al., 2002), is a statistical method used to analyze time-to-event data, particularly in the context of durations until an event occurs or a specific outcome is observed. This approach considers censored data, where the event of interest may not have occurred for some individuals during the study period. The survival function and hazard function are key concepts, providing insights into the probability of events occurring over time.

In the context of the length of time until the first employment for graduates, let T be the non-negative random variable, initiating at $T = 0$ when graduates commence their job search immediately after graduation and concluding at $T = t$ when they secure their first job. The survival function, denoted as $S(t) = P(T > t)$, represents the probability that a graduate remains unemployed beyond time t. The survival function offers insights into the cumulative probability of remaining unemployed over time. The hazard function, denoted as $\lambda(t)$, characterizes the instantaneous failure rate at time t, providing a measure of the risk of finding employment at any given moment. The hazard function can be expressed as the ratio of the probability density function $f(t)$ to the survival function $S(t)$ and this relationship is known as the instantaneous hazard rate. Mathematically, it is given by:

$$\lambda(t) = \frac{f(t)}{S(t)}$$

In this context, $f(t)$ represents the probability density function, which describes the likelihood of a graduate transitioning to employment at a specific time t and $S(t)$ is the survival function, indicating the probability of remaining unemployed beyond time t. This formulation is appropriate for survival analysis, providing a dynamic understanding of the risk of the event (finding employment) occurring at any given moment during the waiting time. The hazard function is a crucial component in modeling the time-to-event data, offering insights into the temporal dynamics of graduates' transition from education to employment.

Non-parametric Method

In this study, the Kaplan-Meier estimator which was proposed by (Schemper & Henderson, 2000), a non-parametric method, was applied to analyze the waiting time to first employment for graduates. The rank-ordered waiting times (t_i, t_{i+1}) representing the duration from graduation to securing the first job, were used to construct the survival function, denoted as $S(t)$. The Kaplan-Meier estimator used was:

$$S(t) = \prod_{i:t_1 \leq t} \left(1 - \frac{d_i}{n_i}\right)$$

Where di is the number of graduates who experienced the event (found employment) at time ti, and ni is the number of graduates at risk of the event just before time t_i.

The Kaplan-Meier estimator provided a step-by-step computation of $S(t)$ by considering the observed waiting times and accounting for censored observations. This non-parametric approach allowed for a robust estimation of the cumulative probability of remaining unemployed over time, offering a clear representation of the temporal dynamics of graduates' employability.

Cox Proportional-Hazards (Cox PH)

The Cox Proportional-Hazards (Cox PH) model is a survival regression model widely used in analyzing time-to-event data. It assesses the hazard or risk of an event occurring at any given time, allowing for the examination of covariate effects on this hazard. In the context of our study on graduates' waiting time to first employment, the Cox PH model enables us to understand how various factors influence the likelihood of finding a job over time. This model is particularly suitable for handling censored observations and does not assume a specific distribution for the survival times.

In our specific case, the covariates in the Cox PH model were defined based on the characteristics of the graduates, such as demographic factors (age, gender), program taken, and job searching methods. The event of interest is the time until graduates secure their first employment, and the hazard function captures the instantaneous risk of this event occurring at any given time. The formula used to assess the hazard of finding employment is as follows:

$$h(t \mid X) = h_0(t) \exp(\beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_k X_k)$$

Where $h(t \mid X)$ the hazard function at time t given the covariates is X, $h_0(t)$ is the baseline hazard function, and $\beta_1, \beta_2, \beta_3, \ldots \beta_k$ are the regression coefficients associated with covariates $X_1, X_2, X_3, \ldots, X_k$. The coefficients quantify the impact of each covariate on the hazard, providing insights into the factors influencing employability over time. The $Cox\ PH$ model is chosen for its flexibility in handling censored observations and its ability to capture time-varying covariate effects. The study also employed a comprehensive examination of residuals, including Schoenfeld residuals for assessing proportional hazards, Cox-Snell residuals for overall model fit, and deviance residuals for scrutinizing predicted event times. These residuals were pivotal in evaluating the Cox Proportional-Hazards model's performance in capturing the waiting time to first employment for graduates.

Accelerated Failure Time (AFT)

The Accelerated Failure Time (AFT) model was employed for parametric survival analysis. The AFT model assumes that the logarithm of the survival time is linearly related to covariates, allowing for a flexible representation of the survival distribution. The specific formula used in this study is expressed as:

$$\log T = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_k X_k + \sigma\epsilon$$

Where T is the survival time (waiting time to first employment), α is the intercept term (allows the model to account for the baseline hazard when there is no influence from the covariates.) $\beta_1, \beta_2, \beta_3, \ldots \beta_p$ are the coefficients representing the effect of covariates $X_1, X_2, X_3, \ldots, X_p$, σ is the scale parameter (accounts for variations in the scale of the survival time distribution, making the model more flexible in capturing different patterns of survival,) and ϵ is the error term.

In the Accelerated Failure Time (AFT) model, the choice of distributional assumption is crucial for reliable estimations. The AFT model assumes that the logarithm of survival time ($\log T$) follows a specified distribution. One common distribution used in AFT modeling is the Weibull distribution, characterized by its flexibility to capture a range of hazard functions, including increasing, decreasing, and constant hazards. The choice of the Weibull distribution in AFT modeling aligns with its versatility and applicability in modeling survival data. Its flexibility allows capturing various shapes of survival curves, making it a suitable choice for analyzing waiting times to first employment in the context of graduates' career transitions. This distributional choice ensures that the AFT model can adequately represent the underlying survival dynamics and provides meaningful insights into the factors influencing time-to-employment outcomes for graduates.

Akaike's Information Criterion

Model selection in survival analysis involves choosing between competing models to identify the one that best fits the data. Akaike's Information Criterion (AIC) introduced by is a widely used measure for model selection, balancing goodness of fit with the complexity of the model. In this study, we will employ AIC to compare the Cox Proportional-Hazards (Cox PH) model and the Accelerated Failure Time (AFT) model. AIC is calculated as:

$$AIC = -2\log L + 2(k + c + 1)$$

Where L is the likelihood of the model, k is the number of covariates or parame- ters in the model, and c is the penalty term associated with the specific distribution parameter (helps to prevent overfitting by discouraging the inclusion of too many parameters that may fit the data well but are not necessarily informative or generalizable to new data). The model with the lowest AIC is considered the most appropriate, indicating a good trade-off between fit and simplicity. We estimate the AIC for both the Cox PH and AFT models and select the one with the lower AIC value as shown in Table 1

Table 1 : Model Comparison of Cox PH and AFT models using AIC values

Model	AIC
Cox PH	6056.76
Weibull	600.93
Exponential	1125.73
Log Normal	634.99
Log Logistic	727.67

This model selection process ensures that the chosen model provides a representation of the survival data while capturing the essential features of waiting times to first employment for graduates. AIC serves as a valuable criterion in determining the optimal model for the analysis.

RESULTS AND DISCUSSION

Explanatory Analysis Using Nonparametric Methods

The Kaplan-Meier curve revealed a median time of 10 months for graduates to secure their first employment after graduation, while the unemployment rate curve consistently remained below the 50% median line after this 10-month threshold, suggesting a positive trend in employment outcomes. This information is visually represented in Figure 1, providing a comprehensive overview of the study's significant findings.

To depict the distribution of graduates' waiting time to first employment across various covariates, Kaplan-Meier curves were employed. These covariates include gender, programs studied, age, and employment search strategies. During the initial 9 months following graduation, the unemployment rate curve for male graduates consistently remained below that of their female counterparts. This suggests a gender-based disparity in the waiting time for securing initial full-time employment. Figure 2 highlights a significant temporal difference in employability between male and female graduates. Such insights into the dynamics of post-graduation employment outcomes based on gender are crucial for understanding and addressing disparities in workforce entry. Figure 3 reveals nuanced patterns in the unemployment rate curves for graduates across various engineering programs. Notably, the curve for Electrical and Automation Engineering dips below the median line after 5 months post-graduation, followed by Electrical and Biomedical Engineering at 7 months, Civil and Highway Engineering at 8 months, and Computer Science at 9 months. These program-specific trends suggest divergent timelines for graduates to secure their first full-time employment. Recognizing these variations is crucial for tailoring targeted interventions and support mechanisms to enhance the employability outcomes of graduates in different engineering disciplines. As shown in Figure 4, the Kaplan-Meier curve unveils noteworthy distinctions in unemployment duration among different age groups. Specifically, graduates aged 25-34 exhibit a curve consistently below the median line after 8 months, indicating a relatively shorter waiting time for securing their initial employment. Similarly, those aged 35 and above experience a curve below the median line after 9 months.

In contrast, graduates aged 15-24 depict a curve persistently above the median line, indicative of a comparatively prolonged waiting period for employment. In the Kaplan-Meier curve presented in Figure 5, the unemployment rate curves for different employment search strategies exhibit distinct patterns. Notably, the curve for internet searching consistently remains below the median line after seven months, suggesting a quicker transition to employment for graduates employing online job search methods. Similarly, the curve associated with relatives, friends, or colleagues as a job search strategy falls below the median line after eight months, indicating a relatively shorter unemployment duration for those utilizing personal networks. In contrast, the curves for Newspaper/Television/Radio, Industry linkage during training, Referral and School endorsement, and Social Media remain above the median line, suggesting prolonged unemployment for graduates employing these methods. The findings underscore the effectiveness of internet and personal network-based job search strategies in facilitating quicker employment transitions.

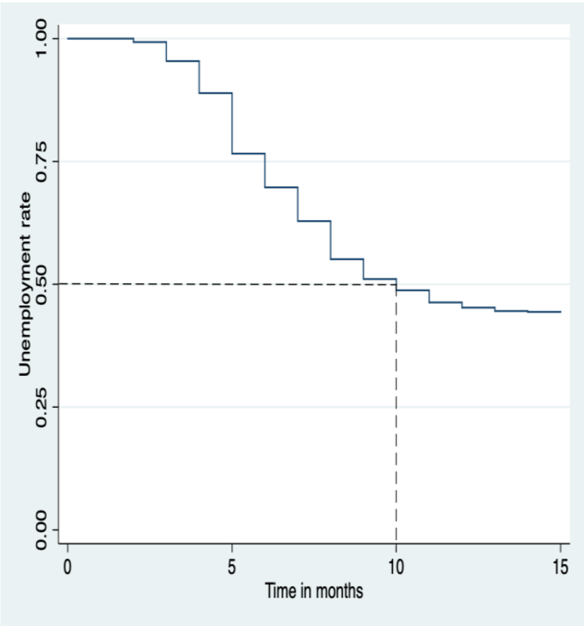

Figure 1 Unemployment time of graduates

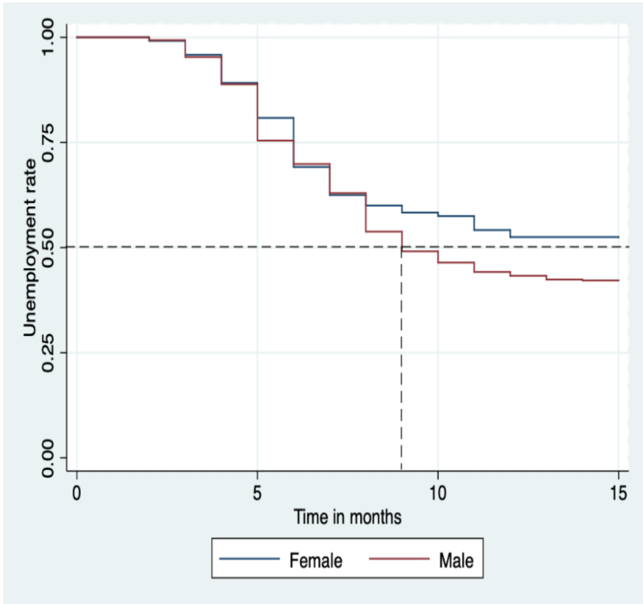

Figure 2 Unemployment time of graduates according to Gender

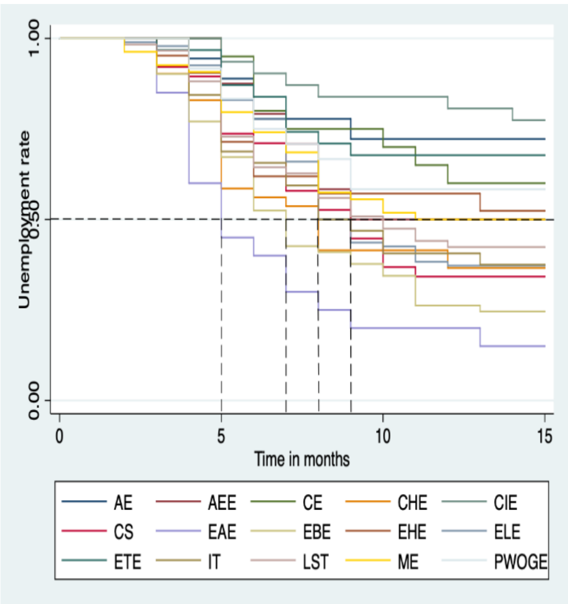

Figure 3 Unemployment time of graduates according to program of study

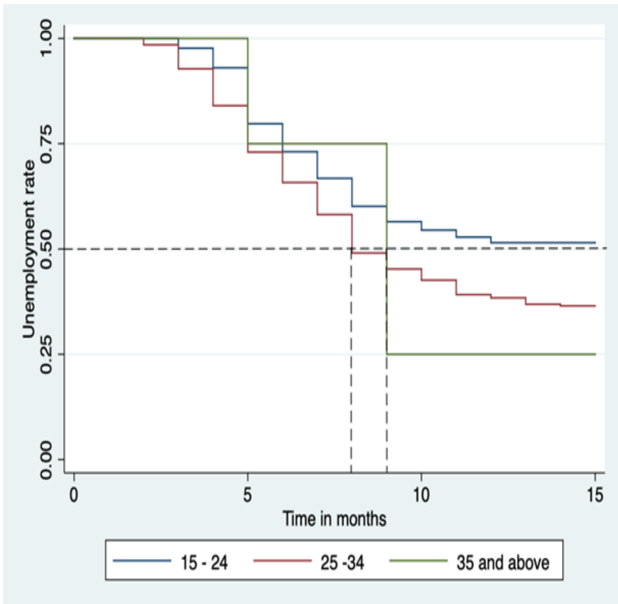

Figure 4 Unemployment time of graduates according to age

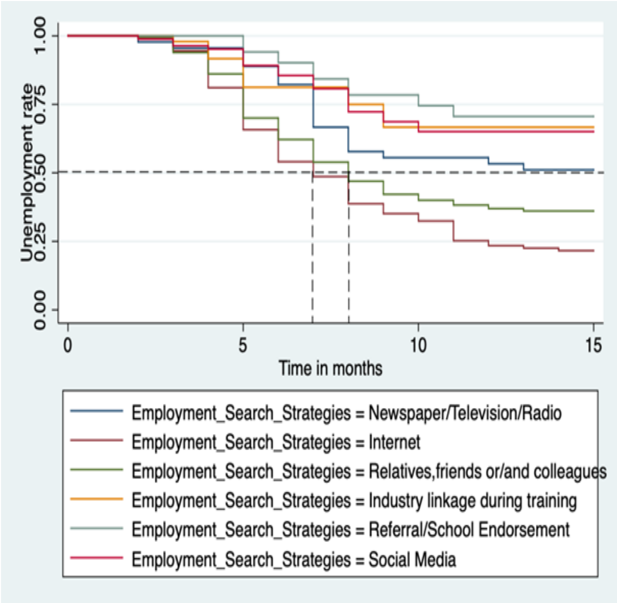

Figure 5 Unemployment time of graduates according to employment search strategies

Cox Proportional Hazard Model Results

The Cox Proportional-Hazards (PH) model revealed a Hazard Ratio (HR) of 1.2675 for gender, and the associated p-value was 0.105. The non-significant p-value indicates that the observed gender difference in the hazard of obtaining the first employment is not statistically significant at the conventional significance level ($p < 0.05$). In practical terms, this implies that the effect of gender on the time to secure employment is uncertain and may be attributed to random variability. The Cox Proportional-Hazards (PH) model yielded a Hazard Ratio (HR) of 1.4734 for the age group 25-34, with the reference being the age group 15-24. The associated p- value of 0.001 is statistically significant, indicating a substantial difference in the hazard of obtaining the first employment between the two age groups. This suggests that individuals in the age range of 25-34 have a significantly higher or lower risk of securing employment compared to those in the reference age group. The lower p-value supports the notion that age is a meaningful predictor of the time it takes to attain employment after graduation. Further exploration and interpretation of this result could shed light on the specific dynamics influencing the employment out- comes of different age cohorts. The Cox Proportional-Hazards (PH) model revealed statistically significant differences in the hazard of obtaining the first employment among various programs. Specifically, for the programs CHE, CS, EAE, EBE, and IT, the p-values were 0.020, 0.028, 0.001, 0.004, and 0.039, respectively, with the reference being the AE program. These results suggest that graduates from the mentioned programs experience significantly distinct employment trajectories compared to those from the AE program. The programs with p-values below the conventional significance threshold of 0.05 indicate a meaningful impact on the time to secure employment. In contrast, programs with p-values exceeding 0.05 may not exhibit statistically significant differences in their employment hazard compared to the reference program. The Cox PH model indicated statistically significant differences in the hazard of obtaining the first employment based on the searching strategies used by graduates. Specifically, the p-values for Internet and relative or friends and colleagues were 0.002 and 0.05, respectively, with the reference being Newspaper. These results suggest that graduates who utilized Internet searching had a significantly different employment hazard compared to those who relied on Newspaper searching. However, searching strategies with p-values exceeding 0.05 may not exhibit statistically significant differences in their employment hazard compared to the reference strategy (Newspaper). The findings underscore the importance of the chosen job-searching method in influencing the time to secure employment for graduates. These information are stipulated in Table 2, Table 3, and Table 4.

Cox Proportional Hazard Assumption Test

The results of the Cox proportional hazards assumption tests indicated the following findings: for Gender, the estimated correlation coefficient (Rho) was 0.05914, with a chi-square test statistic of 1.11 and 1 degree of freedom (df), yielding a probability ($Prob$) greater than chi-square of 0.2922, suggesting no violation of the assumption. Similarly, for Age Interval, the Rho was 0.00041, the chi-square statistic was 0.00 with 1 df, and the Prob>chi-square was 0.9943, indicating no violation.

Regarding Program Studied, the Rho was 0.00252, the chi-square statistic was 0.00 with 1 df, and the Prob>chi-square was 0.9669, indicating no violation. For Employment, the Rho was -0.02051, the chi-square statistic was 0.11 with 1 df, and the Prob>chi-square was 0.7391, again indicating no violation. Finally, the global test resulted in a chi-square statistic of 1.29 with 4 df, and a Prob>chi-square of 0.8632, further supporting the absence of violation of the Cox proportional hazards assumption. The results are as shown in Table 5 below.

Table 2*:* Cox Proportional Hazard Assumption Test Results

Covariates	Rho	$Chi2$	df	$Prob > Chi2$
Gender	0.05914	1.11	1	0.2922
Age Interval	0.00041	0.00	1	0.9943
Program Studied	0.00252	0.00	1	0.9669
Employment Searching Strategies	-0.02051	0.11	1	0.7391
Global Test		1.29	4	0.8632

Table 3 : Distribution of graduates' employment status by selected variables (GTS, 2022)

		Employment Status of Graduates		
Variables	**Categories**	**Unemployed N (%)**	**Employed N (%)**	**TOTAL**
Gender of Graduates	Female	63 (52.5%)	57 (47.5%)	120
	Male	259 (57.8%)	189 (42.2%)	448
Program of Study	ELE	35 (37.2%)	59 (62.8%)	94
	ETE	21 (67.7%)	10 (32.3%)	31
	EBE	15 (24.6%)	46 (75.4%)	61
	EAE	03 (15.0%)	17 (85.0%)	20
	EHE	11 (52.4%)	10 (47.6%)	21
	AEE	12 (50.0%)	12 (50.0%)	24
	AE	13 (72.3%)	05 (27.7%)	18
	CE	12 (60.0%)	08 (40.0%)	20
	CIE	24 (77.4%)	07 (22.6%)	31
	CHE	15 (36.6%)	26 (63.4%)	41
	CS	13 (34.2%)	25 (65.8%)	38
	IT	12 (37.5%)	20 (62.5%)	32
	ME	27 (50.0%)	27 (50.0%)	54
	PWOGE	14 (58.4%)	10 (41.6%)	24
	LST	25 (42.4%)	34 (57.6%)	59
Ways of Searching	Newspaper/Television/Radio	549 (96.7%)	19 (3.3%)	568
	Internet (Government website, company website)	467 (82.2%)	101 (17.8%)	568
	Relatives, friends or/and colleague	442 (77.8%)	126 (22.2%)	568
	Industry Linkage	546 (96.1%)	22 (3.9%)	568
	Referral/School endorsement	555 (97.7%)	13 (2.3%)	568
	Social Media (e.g. Facebook, WhatsApp)	548 (96.5%)	20 (3.5%)	568
Age-Interval	15-24	155 (51.5%)	146 (48.5%)	301
	25-34	96 (36.5%)	167 (63.5%)	263
	35 and Above	1 (25.0%)	03 (75.0%)	4

Table 4*:* Analysis of associated factors of unemployment time based on Cox PH Model, (GTS, 2022)

Cox PH Model		
Covariates	HR [95% CI]	P – Value
Gender (Reference: Female)		
Male	1.267503 (0.9514142, 1.688605)	0.105
Age (Reference: Age group 15-24)		
25 – 34	1.473366 (1.179814, 1.839958)	0.001
35 and above		
Program Graduate Studied (Reference AE)		
AEE	1.943732 (0.6846821, 5.518028)	0.212
CE	1.428452 (0.4673033, 4.366492)	0.532
CHE	3.111714 (1.194606, 8.105406)	0.020
CIE	0.7480412 (0.2374142, 2.356917)	0.620
CS	2.929841 (1.121308, 7.655322)	0.028
EAE	5.805701 (2.139836, 15.75175)	0.001
EBE	3.943885 (1.56642, 9.929796)	0.004
EHE	2.014712 (0.6885971, 5.894689)	0.201
ELE	2.623505 (1.052662, 6.538449)	0.038
ETE	1.180736 (0.403575, 3.454471)	0.762
IT	2.814302 (1.056046, 7.499949)	0.039
LST	2.497857 (0.9768158, 6.387376)	0.056
ME	2.047563 (0.7884631, 5.317324)	0.141
PWOGE	1.621253 (0.5541334, 4.74337)	0.378
Employment Search Strategies (Reference: Newspaper)		
Internet (e.g., government websites)	2.096108 (1.312469, 3.347635)	0.002
Relative, friends or/and colleagues	1.557583 (0.9949436, 2.438395)	0.053
Industry linkages during training	0.6411836 (0.3367016, 1.221011)	0.176
Referral / School Endorsement	0.5240763 (0.2718447, 1.010341)	0.054
Social media (e.g., Facebook, WhatsApp)	0.6606095 (0.3795258, 1.149869)	0.143

Table 5 Analysis of associated factors of unemployment time based Weibull AFT Model

Cox PH Model		
Covariates	HR [95% CI]	P – Value
Gender (Reference: Female)		
Male	1.335979 (1.002815, 1.77983)	0.048
Age (Reference: Age group 15-24)		
25 - 34	1.543108 (1.235481, 1.927332)	0.000
35 and above	1.903678 (0.6067817, 5.972475)	0.270
Program Graduate Studied (Reference AE)		
AEE	2.167911 (0.7636815, 6.154188)	0.146
CE	1.50906 (0.4936755, 4.612871)	0.470
CHE	3.430851 (1.317072, 8.937053)	0.012
CIE	0.742691 (0.2357182, 2.34004)	0.611
CS	3.425682 (1.310966, 8.951643)	0.012
EAE	6.840195 (2.519692, 18.56904)	0.000
EBE	4.633295 (1.839723, 11.66884)	0.001
EHE	2.086651 (0.7131939, 6.105087)	0.179
ELE	3.079019 (1.235409, 7.67386)	0.016
ETE	1.20511 (0.411911, 3.525737)	0.733
IT	3.161585 (1.186294, 8.425924)	0.021
LST	2.763348 (1.080588, 7.066613)	0.034
ME	2.217362 (0.8538495, 5.758269)	0.102
PWOGE	1.701301 (0.5814955, 4.977553)	0.332
Employment Search Strategies (Reference: Newspaper)		
Internet (e.g., government websites)	2.349873 (1.47079, 3.75438)	0.000
Relative, friends or/and colleagues	1.621146 (1.035516, 2.537976)	0.035
Industry linkages during training	0.6026347 (0.3164839, 1.14751)	0.123
Referral / School Endorsement	0.4961249 (0.2573542, 0.9564245)	0.036
Social media (e.g., Facebook, WhatsApp)	0.6315663 (0.3628537, 1.099275)	0.104

CONCLUSION

In conclusion, this study sheds light on the dynamics of employment outcomes for graduates from Arusha Technical College, employing a comprehensive analysis of survival data. The Kaplan-Meier curves revealed nuanced patterns in the waiting time to first employment based on factors such as gender, age, academic program, and job-searching strategies. The Cox PH model further elucidated the significant impact of these factors on the hazard of obtaining the first employment. Notably, gender differences, age groups, academic programs like Civil and High- way Engineering, Computer Science, Electrical and Automation Engineering, Electrical and Biomedical Engineering, and Information Technology, as well as various job-searching strategies such as Internet and Relative/friends and colleagues, exhibited varying effects on the time to secure employment. The findings underscore the multifaceted nature of employability determinants and emphasize the need for tailored approaches to address distinct challenges faced by graduates. While some factors showed statistically significant associations with the hazard of employment, others did not reach significance levels. This suggests the complexity of employability dynamics and the need for further exploration. The study contributes valuable insights to the literature on graduate employability, providing a basis for informed policy decisions and interventions to enhance employment out- comes for graduates from Arusha Technical College. Future research could delve deeper into specific program-related challenges and explore additional factors influencing the transition from education to employment in the local context.

RECOMMENDATIONS

Based on the findings of this study, several recommendations can be made to improve employment outcomes for graduates from Arusha Technical College:

- Tailored Career Development Programs: Develop targeted career development programs that address the unique needs of different demographic groups, academic programs, and job-searching strategies identified in the study. These pro- grams should provide guidance on resume building, job interview skills, networking opportunities, and industry-specific insights to enhance graduates' employability.
- Strengthen Industry-Academia Collaboration: Foster closer collaboration be- tween academic institutions and industries to ensure that academic programs align with the skills and competencies demanded by the labor market. This can be achieved through internships, industry-sponsored projects, and guest lectures by industry professionals to bridge the gap between theoretical knowledge and practical application.
- Supportive Job Placement Services: Enhance job placement services offered by the college to provide personalized assistance to graduates in their job search process. This could include career counseling, job matching services, and alumni networking platforms to connect graduates with potential employers. Promote Entrepreneurship Opportunities:
- Encourage entrepreneurship among graduates by providing support for startup ventures, business incubation programs, and access to financial resources. Empowering graduates to pursue entrepreneurial endeavors can create alternative pathways to employment and contribute to economic growth and innovation.
- Continuous Monitoring and Evaluation: Implement a system for continuous monitoring and evaluation of graduates' employment outcomes to track their career progression and identify areas for improvement in career services and academic programs. This feedback loop will enable the college to adapt its offerings to meet the evolving needs of graduates and the labor market.

By implementing these recommendations, Arusha Technical College can enhance its graduates' employability and contribute to their successful transition into the workforce, ultimately fostering socio-economic development in the region.

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Data Availability

The data set used in this study are available from the corresponding author upon reasonable request.

Conflict of Interest

All authors declare that there is no conflict of interest.

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