Evaluating the Influence of Education on Current Unemployment Trends*

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March 30, 2024

This paper investigates the relationship between educational attainment and unemployment rates amidst the evolving dynamics of technological advancement and globalization, utilizing data from the Labour Force Survey spanning 2019 to 2023. Our analysis reveals significant variability in unemployment rates across different educational levels, highlighting the nuanced impact of higher education in an era increasingly dominated by artificial intelligence and outsourcing. These findings underscore the critical need for educational systems to adapt, emphasizing skills that complement technological advancements and align with the global job market. Ultimately, this study illuminates the complex interplay between education, employment, and technological change, offering valuable insights for policymakers and educators in preparing the workforce for the challenges of the future labor market.

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*Code and data are available at: LINK

1 Introduction

In recent years, the narrative surrounding employment and the value of higher education has become increasingly complex. Amidst a landscape marked by technological advancements and a globalizing economy, stories of job seekers with advanced degrees facing employment challenges have proliferated. There are even "trends" going around social media on platforms such as TikTok or Instagram, where people are sharing their experience of graduating with a degree, in some cases multiple degrees, and still struggling to find a job or a job that they perceive their degree to be worth (i.e. working as a barista at Starbucks when they have a computer science degree, etc.). News reports often depict long queues for scarce job openings, painting a vivid picture of the competitive and sometimes disheartening job market. This can be seen from news sources such as the `Toronto Sun` (Wilford (2024)), the `blogTO` (Mehrabi (2023)), and many more. This juxtaposition of high educational attainment and employment difficulty raises critical questions about the evolving dynamics of the labor market, the role of education, and the implications for future workforce development.

This paper delves into the nuanced relationship between educational levels and unemployment rates, set against the backdrop of rapid technological change and globalization. By analyzing unemployment trends across various demographics from 2019 to 2023, this study seeks to uncover how different levels of education impact an individual's likelihood of employment. Amid widespread discourse on the diminishing returns of higher education in certain sectors, and the transformative potential of artificial intelligence (AI) and automation to replace traditional jobs, this research aims to provide empirical insights into these phenomena.

A significant gap exists in understanding the real-time implications of these global shifts on employment, particularly in how educational attainment intersects with evolving job market demands. This study addresses this gap by utilizing data from the Labor Force Survey, exploring the interplay between education and unemployment, and considering the external factors influencing these relationships.

The findings reveal varied unemployment rates across educational strata, with notable differences in how higher education correlates with job security in the face of AI integration and outsourcing trends. These results underscore the necessity for a reevaluation of educational objectives and curricula, emphasizing skills that are less susceptible to automation and more aligned with emerging industry needs.

The importance of this research lies in its potential to inform policy decisions and educational strategies, aiming to foster a workforce that is adaptable, skilled, and prepared for the challenges of the future job market. By providing a clearer understanding of the current employment landscape, this paper contributes to the broader discourse on preparing for a labor market in flux.

The paper is structured as follows: Following this introduction, we describe the methodology and data sources used in our analysis in (Section 2). Subsequent sections present the model we estimate (Section 3), and results (Section 4) showcasing the implications of educational attainment on unemployment rates. The paper concludes with a discussion (Section 5) of the findings, limitations, and recommendations for future research and policy considerations.

2 Data

Table 1: Unemployed Dataset from 2019 to 2023 by education level

Education Level	Reference Period	Youth Unemployment	Adult Unemployment	Senior Unemployment
Total, all education levels	2019	10.7	5.1	4.6
Total, all education levels	2020	20.1	8.5	7.4
Total, all education levels	2021	13.5	6.4	6.7
Total, all education levels	2022	10.1	4.6	4.4

Education Level	Reference Period	Youth Unemployment	Adult Unemployment	Senior Unemployment
Total, all education levels	2023	10.8	4.9	4.2
0 to 8 years	2019	17.5	9.4	7.8

The dataset outlined in Table 1 captures a comprehensive view of unemployment rates spanning from 2019 to 2023, segmented by different education levels. This rich dataset provides insights into the unemployment trends for three distinct age groups: youth, adults, and seniors, highlighting how economic fluctuations impact various demographics over time. The granularity of the data allows for an in-depth analysis of how education, as a key socio-economic factor, correlates with employment stability and job market resilience during periods of economic change.

2.1 Data Measurement

Our data set is comprised of data from the `Labour Force Survey` (Canada 2024a). The Labour Force Survey (LFS) is a principal source for the measurement of Canada's labour market activities. Here, we provide an overview of the survey methodology and the robustness of the data collected.

- Survey Design and Methodology
  - The LFS uses a stratified multi-stage sampling approach to gather data from a representative sample of the non-institutionalized civilian population aged 15 and over. The survey design meticulously excludes certain populations, such as full-time military personnel and residents of institutions, ensuring the accuracy and relevance of the labour force estimates.
- Collection and Processing
  - Conducted monthly, the LFS is characterized by its promptness, with data releases occurring just 10 days post-collection. The survey yields the early indicator estimates of employment and unemployment, alongside other vital labour market indicators including the employment rate and participation rate.
- Utilization of Data
  - Governments and policymakers extensively use LFS data to evaluate and plan employment programs. The data are essential for determining eligibility and the level of Employment Insurance benefits, as well as for the analysis conducted by economists, labour market analysts, and researchers.

- Supplementary Surveys
  - In conjunction with the LFS, surveys like the SEPH, EIS, and JVWS contribute to a comprehensive understanding of current labour market conditions, providing a more detailed and nuanced picture.
- Data Collection Techniques
  - Interviews are conducted through computer-assisted methods, either by telephone or in-person visits. This allows for the collection of a diverse set of labour market data, which is further refined through editing and imputation to account for non-responses or inconsistencies.
- Estimation Procedures
  - Sample data are meticulously weighted to produce reliable estimates at the national, provincial, and sub-provincial levels. These weights are adjusted to compensate for non-responses and to align the survey estimates with known population controls.
- Quality Control
  - To ensure the highest data quality, the LFS is subject to rigorous validation against other economic data sources. This includes the comparison of employment estimates with those from SEPH, EIS, and census data.
- Confidentiality and Disclosure Control
  - Adhering to stringent confidentiality rules, the LFS ensures that no individual or business information is disclosed without consent. The survey employs a range of suppression rules to maintain the anonymity of the data.
- Seasonal Adjustment
  - The LFS implements the X-12-ARIMA technique for seasonal adjustment, allowing for the analysis of short-term labour market trends without the influence of seasonal patterns.
- Accuracy and Reliability
  - Despite being subject to sampling errors inherent in survey data, the LFS employs coefficients of variation and other statistical measures to assess and enhance the reliability of its estimates.

This survey's methodology and the rapid release of its results make the LFS a cornerstone in the analysis and understanding of Canada's labour market dynamics.

2.2 Data Analysis

This paper uses the Statistics of Canada `Unemployment rate, participation rate and employment rate by educational attainment, annual` (Canada 2024b) dataset. We are using the `R programming language` (R Core Team 2023) to conduct our analysis along with `readR` (Wickham, Hester, and Bryan 2024), `lubridate` (Grolemund and Wickham 2011), `tidyverse` (Wickham et al. 2019), `dplyr` (Wickham et al. 2023), `tidyr` (Wickham, Vaughan, and Girlich 2023), `knitr` (Xie 2014), `janitor` (Firke 2023), `scales` (Wickham, Pedersen, and Seidel 2023), `RColorBrewer` (Neuwirth 2022), `ggplot2` (Wickham 2016), `kableExtra` (Zhu 2024), `here` (Müller 2020), `arrow` (Richardson et al. 2024), `rstanarm` (Brilleman et al. 2018), `modelsummary` (Arel-Bundock 2022), and `lme4` (Bates et al. 2015).

3 Model

The goal of our modeling strategy, utilizing multiple linear regression, is multifaceted:

- **Understanding Relationships**: To understand the relationship between several independent variables, such as education level and age groups, and the dependent variable, which in this context is the youth unemployment rates. The model is designed to isolate the effect of each variable on unemployment rates.
- **Quantifying Impact**: To quantify the impact of each predictor. Regression coefficients provide a numerical value that represents the expected change in the dependent variable for a one-unit change in an independent variable, all else being equal.
- **Predictive Analysis**: To develop a predictive framework that can be employed to estimate or forecast the outcome variable, in this case, unemployment rates, when provided with new data for the predictors.
- **Inferential Statistics**: To conduct hypothesis testing to ascertain whether the relationships observed within the data are statistically significant and not merely due to random variation.
- **Policy Decision Support**: To offer empirical evidence that may inform policy decisions. For instance, if a correlation is found between higher education levels and increased unemployment, it might indicate the necessity for policies that better align education with employment opportunities.
- **Data-Driven Insights**: To extract insights from the data that could lead to an enhanced understanding of labor market dynamics, such as how different age groups' unemployment rates interact.
- **Modeling Assumptions Testing**: To validate the assumptions underlying the regression model, ensuring the reliability and accuracy of the model's predictions.

- **Confounding Variable Control**: To account for potential confounders that might influence the relationship between education level and unemployment rates. The inclusion of relevant variables aims to minimize estimation bias.
- **Sensitivity Analysis**: To comprehend the model's sensitivity to changes in inputs, which assists in evaluating the robustness of the model.

This strategy is designed to produce a model that is both explanatory and predictive, offering a current snapshot of the relationships in the data as well as a tool for future forecasting. Such a model can be utilized to guide decision-making processes or pinpoint where interventions may be effective.

3.1 Model set-up

$$\begin{aligned}\text{Youth Unemployment} = \beta_0 &+ \beta_1 \cdot \text{Education Level} \\ &+ \beta_2 \cdot \text{Reference Period} \\ &+ \beta_3 \cdot \text{Adult Unemployment} \\ &+ \beta_4 \cdot \text{Senior Unemployment} + \epsilon\end{aligned}$$

Where:

- `Youth Unemployment` is the dependent variable we are trying to predict. These are generally categorized as people who are between the ages of 15-24.
- `Education Level` is an independent variable representing the level of education. (e.g., high school, undergraduate, postgraduate)
- `Reference Period` is another independent variable that represents the time frame of the data collection (e.g., year).
- `Adult Unemployment` and `Senior Unemployment` are independent variables representing unemployment rates for adult and senior age groups, with people ages ranging between 25-44 and above 45, respectively.
- β_0 is the y-intercept, representing the expected value of `Youth Unemployment` when all the independent variables are 0.
- $\beta_1, \beta_2, \beta_3, \beta_4$ are the coefficients for each independent variable, representing the change in `Youth Unemployment` for a one-unit change in the respective independent variable, holding all other variables constant.
- ϵ represents the error term, accounting for the variability in `Youth Unemployment` not explained by the model.

This model aims to understand how various factors contribute to youth unemployment. The coefficients $\beta_1, \beta_2, \beta_3, \beta_4$ provide insights into the relationship between each independent variable and youth unemployment:

- β_1 tells us how changes in the education level might affect youth unemployment, holding other factors constant. A positive coefficient suggests that higher education levels are associated with higher youth unemployment rates, while a negative coefficient suggests the opposite.
- β_2 gives insight into how changes over the reference period (e.g., years) impact youth unemployment, which can help identify trends over time.
- β_3 and β_4 help understand how unemployment rates in other age groups (adults and seniors) are related to youth unemployment. This can reveal whether higher unemployment rates in these groups are associated with higher or lower youth unemployment rates.

The intercept β_0 provides the baseline level of youth unemployment when all other variables are zero, which may not always be a practical scenario but is necessary for the model's mathematical formulation. The error term ϵ captures the model's limitations and any random factors affecting youth unemployment that aren't included in the model.

3.2 Model justification

The utilization of a multiple linear regression model for analyzing the relationship between people's unemployment status, age groups, and education level over time is substantiated by various rationales. Primarily, the model adeptly accommodates multiple independent variables such as education level and age group, each potentially exerting influence on the dependent variable, unemployment status. This capacity allows for an assessment of the individual impact of each predictor while simultaneously controlling for the influence of others. Such a model not only facilitates the quantification of the relationships between these factors and unemployment—via coefficients that express the extent of change in response per unit change in a predictor (with other variables held constant)—but also enables hypothesis testing on the parameters. This testing is instrumental in determining whether the associations between predictors and the response are statistically significant, thereby offering insights into the meaningfulness of these relationships.

4 Results

4.1 Model Interpretation:

Based on the regression model output, as seen in Table 2, several interpretations can be drawn:

- **Baseline Unemployment**: The intercept of 328.01 suggests a baseline youth unemployment level, conditional on all other predictor variables being zero.

Table 2: Regression Analysis: Impact of Education Level and Age on Youth Unemployment

	Baseline Model for Youth Unemployment
(Intercept)	328.01
	(368.38)
Above Bachelor's	5.14
	(1.40)
Bachelor's	4.14
	(1.37)
High School Grad	−0.41
	(1.16)
Postsec. Cert/Dip	1.24
	(1.29)
Some High School	−0.95
	(1.10)
Some Postsec.	−2.20
	(1.28)
All Levels	4.55
	(1.25)
University	4.27
	(1.37)
Reference Period	−0.16
	(0.18)
Adult Unemployment	2.19
	(0.31)
Senior Unemployment	−0.20
	(0.37)
Num.Obs.	45
R2	0.923
R2 Adj.	0.898
AIC	182.4
BIC	205.9
Log.Lik.	−78.222
RMSE	1.38

- **Impact of Higher Education**:
  - *Above Bachelor's Degree*: The coefficient 5.14 indicates a significant and positive association with youth unemployment rates, implying potential overqualification or job market mismatches.
  - *Bachelor's Degree*: Similarly, a coefficient of 4.14** suggests that a bachelor's degree is associated with higher unemployment.
  - *University Degree*: With a coefficient of 4.27, university graduates also face higher unemployment rates.
- **Some Postsecondary Education**: A negative coefficient of -2.20 for those with some postsecondary education indicates a decrease in unemployment compared to the reference group.
- **Adult Unemployment**: The significant positive coefficient 2.19 for adult unemployment implies a correlation with youth unemployment rates.
- **Time Factor**: The non-significant coefficient for the reference period suggests that time does not significantly alter youth unemployment rates when holding other factors constant.
- **Goodness of Fit**:
  - The high R-squared value of 0.923 indicates that the model explains much of the variance in youth unemployment rates.
  - The Adjusted R-squared value of 0.898 takes into account the number of predictors and suggests a good fit to the data.

These findings underscore the complexity of youth unemployment and the varied impact of educational attainment on job market outcomes.

4.2 Youth Unemployment

The results presented in Table 3 and Table 4 shows the percentage change of youth unemployment rates over the years by education level for 2019-2023 and 2022-2023 respectively. The column on the far right shows the net percentage change for that time period.The following formula was used to calculate the net percentage change in the unemployment rate:

$$\text{Net Percentage Change} = \left(\frac{\text{Value at End Period} - \text{Value at Start Period}}{\text{Value at Start Period}}\right) \times 100\%$$

Table 3: Percentage Change in Youth Unemployment by education level (2019-2023)

Education Level	Unemployment Rate (2019)	Unemployment Rate (2023)	Percentage Change (%)
0 to 8 years	17.5	18.6	6.29
Above bachelor's degree	10.3	9.3	-9.71
Bachelor's degree	7.7	8.5	10.39
High school graduate	10.9	11.2	2.75
Postsecondary certificate or diploma	6.7	6.4	-4.48
Some high school	16.8	16.8	0.00
Some postsecondary	9.8	9.1	-7.14
Total, all education levels	10.7	10.8	0.93
University degree	8.0	8.6	7.50

Table 4: Percentage Change in Youth Unemployment by education level (2022-2023)

Education Level	Unemployment Rate (2022)	Unemployment Rate (2023)	Percentage Change (%)
0 to 8 years	15.0	18.6	24.00
Above bachelor's degree	8.8	9.3	5.68
Bachelor's degree	7.6	8.5	11.84
High school graduate	10.6	11.2	5.66
Postsecondary certificate or diploma	6.7	6.4	-4.48
Some high school	14.9	16.8	12.75
Some postsecondary	8.5	9.1	7.06
Total, all education levels	10.1	10.8	6.93
University degree	7.7	8.6	11.69

Looking at Figure 1, it gives us a visualization of the youth unemployment rates for varying education levels across the years. We then used the following formula to calculate the overall percentage change between years:

$$\text{Overall Percentage Change} = \left(\frac{\text{Sum of Rates in X Year} - \text{Sum of Rates in Y Year}}{\text{Sum of Rates in Y Year}} \right) \times 100\%$$

The overall percentage change for the youth unemployment rate is $\approx 0.92\%$ increase between 2019 and 2023 and $\approx 10.45\%$ increase between 2022 and 2023.

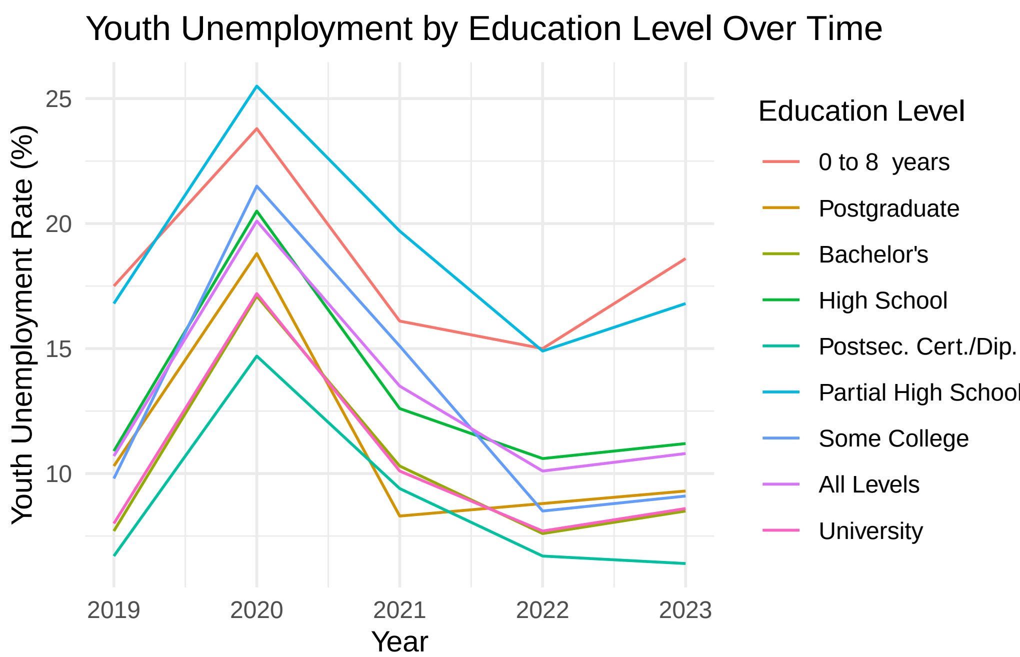

Figure 1: Youth Unemployment Rates

The figures and tables from our analysis present a nuanced picture of youth unemployment across different educational strata over a period extending from 2019 to 2023.

- **Trends Over Time**: A clear pattern of fluctuation is evident in the unemployment rates. The peak observed in 2020 may correlate with the economic downturn caused by the COVID-19 pandemic, affecting youth employment disproportionately.
- **Impact of Education**: The variation in unemployment by education level underscores the importance of educational attainment. Notably, higher levels of education such as “Above Bachelor’s” and “Bachelor’s” do not necessarily correlate with lower unemployment rates, suggesting a potential oversupply of higher education qualifications or mismatches between education and job market needs.
- **Percentage Changes**:
  - *Net Percentage Change*: Individual educational levels show diverse trends, with some experiencing increases in unemployment, while others show decreases over the four-year span.
  - *Overall Percentage Change*: The aggregate data reveals a modest uptick in youth unemployment rates, which may reflect broader economic and societal shifts.

4.3 Adult Unemployment

Table 5: Percentage Change in Adult Unemployment by education level (2019-2023)

Education Level	Unemployment Rate (2019)	Unemployment Rate (2023)	Percentage Change (%)
0 to 8 years	9.4	11.3	20.21
Above bachelor's degree	4.4	4.0	-9.09
Bachelor's degree	4.1	4.2	2.44
High school graduate	7.1	7.1	0.00
Postsecondary certificate or diploma	4.4	4.3	-2.27
Some high school	9.9	9.6	-3.03
Some postsecondary	7.1	6.7	-5.63
Total, all education levels	5.1	4.9	-3.92
University degree	4.2	4.1	-2.38

Table 6: Percentage Change in Adult Unemployment by education level (2022-2023)

Education Level	Unemployment Rate (2022)	Unemployment Rate (2023)	Percentage Change (%)
0 to 8 years	8.5	11.3	32.94
Above bachelor's degree	3.5	4.0	14.29
Bachelor's degree	3.8	4.2	10.53
High school graduate	6.5	7.1	9.23
Postsecondary certificate or diploma	4.1	4.3	4.88
Some high school	9.9	9.6	-3.03
Some postsecondary	6.5	6.7	3.08
Total, all education levels	4.6	4.9	6.52
University degree	3.7	4.1	10.81

Similar to youth unemployment, Table 5, and Table 6 show the net percentage change in adult unemployment for the years 2019-2023 and 2022-2023 respectively.

The analysis of adult unemployment rates from 2019 to 2023 uncovers distinct trends across education levels. Notably, individuals with "0 to 8 years" of education show a marked increase in unemployment rates, which could indicate that lower educational attainment is a significant risk factor for adult unemployment.

Conversely, adults with education "Above a bachelor's degree" experienced a decrease in unemployment rates, suggesting that higher education may offer better protection against job

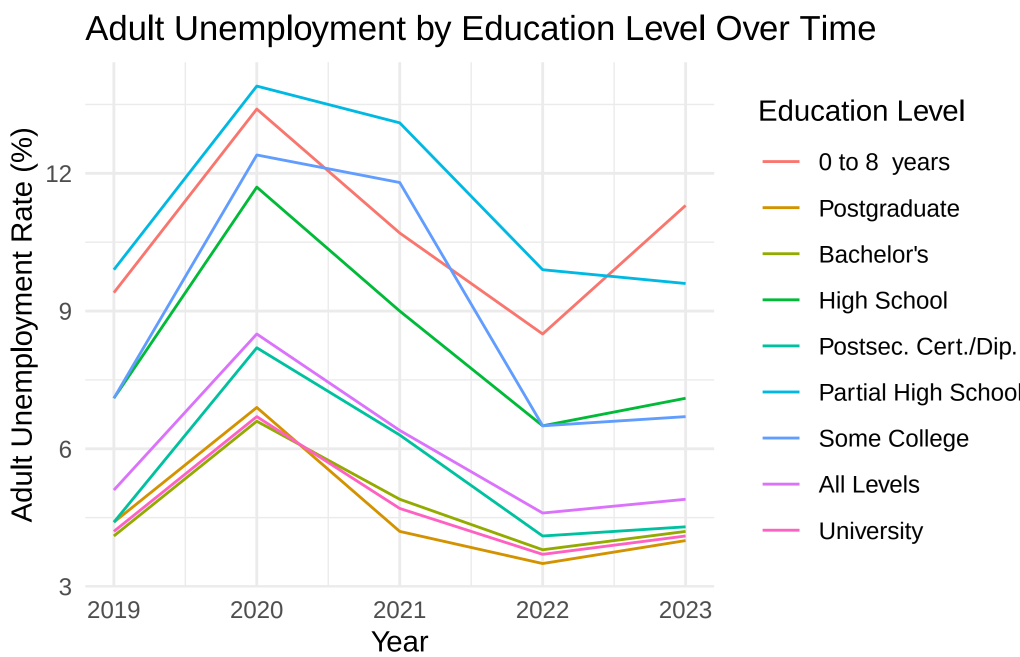

Figure 2: Adult Unemployment Rates

market downturns. This trend aligns with the expectation that higher qualifications translate to greater employment stability.

For other education categories, such as “Bachelor’s degree” and “High school graduate,” the changes are relatively moderate, indicating a more nuanced relationship between education and job market outcomes for these groups.

Overall, the adult unemployment rate shows an approximately $\approx 0.89\%$ increase from 2019 to 2023, which might reflect the lingering effects of economic events or shifts in the labor market dynamics. However, the period from 2022 to 2023 sees a more pronounced increase of approximately $\approx 9.98\%$, highlighting the potential for rapid changes in unemployment within a single year.

These patterns underscore the importance of ongoing education and training throughout one’s career, as well as the need for targeted support for adults with lower levels of education.

Figure 2 illustrates the fluctuation in unemployment rates across different education levels. It reveals that unemployment is not uniform across the educational spectrum, which has implications for policymakers and educators alike.

4.4 Senior Unemployment

Table 7: Percentage Change in Senior Unemployment by education level (2019-2023)

Education Level	Unemployment Rate (2019)	Unemployment Rate (2023)	Percentage Change (%)
0 to 8 years	7.8	7.1	-8.97
Above bachelor's degree	3.2	3.6	12.50
Bachelor's degree	3.8	3.7	-2.63
High school graduate	4.8	4.4	-8.33
Postsecondary certificate or diploma	4.6	4.0	-13.04
Some high school	7.0	6.8	-2.86
Some postsecondary	4.8	4.0	-16.67
Total, all education levels	4.6	4.2	-8.70
University degree	3.6	3.7	2.78

Table 8: Percentage Change in Senior Unemployment by education level (2022-2023)

Education Level	Unemployment Rate (2022)	Unemployment Rate (2023)	Percentage Change (%)
0 to 8 years	8.0	7.1	-11.25
Above bachelor's degree	3.3	3.6	9.09
Bachelor's degree	3.7	3.7	0.00
High school graduate	4.9	4.4	-10.20
Postsecondary certificate or diploma	4.3	4.0	-6.98
Some high school	7.6	6.8	-10.53
Some postsecondary	4.4	4.0	-9.09
Total, all education levels	4.4	4.2	-4.55
University degree	3.6	3.7	2.78

The study of senior unemployment sheds light on the intricate interplay between education levels and job market viability. Key observations include:

- **Divergent Patterns**: A pronounced decrease in unemployment rates was observed among seniors with vocational training as seen from Table 7 and Table 8, while those with higher academic degrees saw an uptick, raising questions about the alignment between higher education and job opportunities in the market.
- **Consistency Among University Graduates**: Seniors holding university degrees experienced a marginal increase in unemployment, suggesting a relative consistency within this group compared to others.

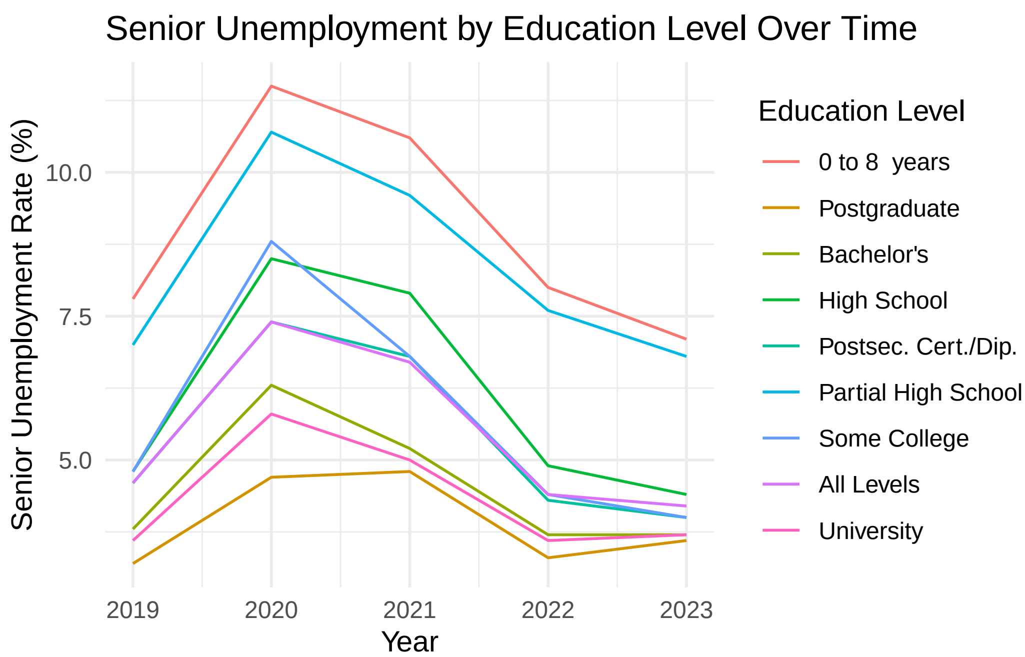

Figure 3: Senior Unemployment Rates

- **Overall Shifts**: There was an overall reduction in senior unemployment from 2019 to 2023 with a decrease of approximately $\approx 13.54\%$ and a decrease of approximately $\approx 6.11\%$ from 2022 to 2023, pointing towards potential shifts in retirement age, economic recoveries, or evolving job opportunities for seniors.
- The overarching trends in senior unemployment call for strategic educational planning and job placement efforts tailored to the nuanced needs of the aging workforce.
- The plotted data shown in Figure 3 provides a visual narrative of unemployment trends among seniors, highlighting that educational achievements translate differently into job security for the senior population.

5 Discussion

5.1 What we learn from these results

From the results of our analysis, two key insights emerge that expand our understanding of the global labor market and its interplay with education.

5.1.1 The Impact of Education on Employment

Our data distinctly reveals that education significantly influences employability. The variation in unemployment rates across educational levels underlines the fact that not all education is equal in the eyes of the labor market. Higher education levels often correlate with lower unemployment rates, suggesting that advanced skills and qualifications can provide an edge in securing employment. This aligns with the longstanding view that educational attainment can enhance an individual's job prospects, potentially leading to more stable and higher-quality employment opportunities.

However, the data also highlight that higher education does not guarantee immunity against unemployment. This could be due to a myriad of factors, including the mismatch between the skills acquired through higher education and the needs of the job market, or possibly the saturation of certain degrees in the labor force. A great example of this is the computer science job market. People trying to get into the computer science job market are faced with the harsh reality of not being able to find a job. In fact, "Computer Science Students Face a Shrinking Big Tech Job Market" (Singer and Huang (2022)) according to the NY Times "Hiring in tech, information, and media is at its lowest level since July 2020" (Ingram (2022)). With these graduate students seeking to find a job, they are most likely to go into an "entry-level position", if they even exist regardless of the field they are pursuing. The emphasis here is that these entry-level positions are either not existent, or the people working these jobs are majorly over-qualified. This does not even account for the number of layoffs that happen on a regular basis from these major tech companies. A very recent major layoff is from Bell Communications where they played off "hundreds of employees in 10-minute video call meetings" (T. T. Desk (2024)) and that "no union reps or members were allowed to unmute themselves during the call and ask anything" (Staff (2024)). Thus, while education is a powerful tool for improving employment prospects, it is not a panacea. There is a need for ongoing evaluation of educational curricula to ensure alignment with evolving industry demands.

5.1.2 The Resilience of Different Demographics

The study also sheds light on the resilience of various demographic groups in the face of economic fluctuations. Individuals with vocational training, in particular, demonstrate robustness in maintaining employment, potentially due to the practical nature of their skills and the specific demand for trades in the economy. Similarly, those with higher education—despite facing some challenges—often show a lesser impact from economic downturns, indicating that higher education may still provide a buffer against the vagaries of the job market.

These observations suggest that the job market values not just education but the relevance and applicability of the skills obtained. In other words, people are granted "seniorities", hence why they are seen as more valuable to a company. As economies evolve and new industries emerge, the adaptability of the workforce becomes crucial. Hence, continuous learning and skills development are imperative for both individuals and economies to thrive.

5.2 Why are we seeing these results

The patterns observed in unemployment rates across educational levels may be attributable to several underlying factors. Understanding why we see these results requires delving into the interconnections between educational systems, economic structures, and labor market demands.

5.2.1 Educational System Alignment with Market Needs

A potential reason for the variation in unemployment rates could be the degree to which education systems are aligned with current market needs. Educational institutions that closely work with industries and update curricula to reflect technological advancements and market trends may better equip students with marketable skills. On the other hand, a mismatch between graduates' skills and job requirements can lead to higher unemployment rates, even among those with advanced degrees.

5.2.2 Economic Shifts and Job Market Evolution

The global economy is in a constant state of flux, influenced by technological change, globalization, and, more recently, by the impact of the COVID-19 pandemic. A recent news article publishing the tech sector layoffs from companies such as Apple, Dell, IBM, and many more states that "the tech industry's wave of layoffs shows no signs of slowing down as we enter the latter half of March 2024. Major players across the sector are still downsizing their workforces as economic headwinds persist" (T. Desk (2024)). These economic shifts can create or eliminate entire industries, affecting employment opportunities differently across educational levels. The growing emphasis on technology might benefit those with relevant qualifications while displacing jobs in sectors less adaptable to these changes. This leads into my next point.

5.2.3 The Influence of Artificial Intelligence on the Job Market

The impact of artificial intelligence (AI) on the job market is multifaceted and profound, acting as both a disruptor and a catalyst within the labor landscape. AI's capacity for automating tasks has resulted in the displacement of certain jobs, particularly those involving routine and repetitive functions. However, it's equally notable for creating new job categories that necessitate human oversight and management of these advanced systems. As AI redefines roles, the urgency for upskilling becomes apparent—workers are finding themselves in need of new competencies that align with the evolving demands of an AI-integrated workplace. The skills that are becoming increasingly indispensable are those that AI cannot easily replicate, such as complex problem-solving, critical thinking, and creative capacities. These skills highlight the enduring value of human ingenuity in the age of automation.

Furthermore, AI's contribution to economic efficiency and productivity has the potential to spur economic growth, indirectly fostering job creation with a shift in required skill sets. The onus is on policymakers to navigate this transition, balancing the embrace of technological innovation with the need for robust support systems for the workforce. They face the challenge of creating policies that not only protect workers from the immediate risks of displacement but also encourage the development of industries poised to grow in the AI era. Ultimately, the integration of AI into the economy presents a complex narrative: while it may render some occupations obsolete, it simultaneously opens doors to new realms of employment. The key challenge—and opportunity—lies in harnessing AI as a tool to enhance human work, not replace it, by anticipating changes and preparing the workforce through education and training to thrive alongside intelligent machines.

5.2.4 Job outsourcing

The globalization of the labor market has seen an increasing trend in companies outsourcing work internationally, driven by the quest for cost reduction, efficiency gains, and access to a broader talent pool. Outsourcing has become a strategic move for businesses looking to streamline operations and focus on core competencies while delegating peripheral activities to external specialists. This shift has had a significant impact on the job market.

Outsourced jobs often transition from higher-cost labor markets to regions where labor costs are lower, fundamentally altering the employment landscape in both the originating and recipient countries. While outsourcing can lead to job losses in some sectors within developed economies, it simultaneously generates employment opportunities in developing regions. This redistribution of jobs raises questions about the long-term sustainability of such practices, considering the potential for economic disparity and the need for international labor standards. Recently, Canada Life is said to be cutting out their IT department and is instead "Outsourcing work to a tech company headquartered in India" (Piché (2024)), again where labor costs are much cheaper.

The implications for the domestic workforce are considerable. Jobs that are more vulnerable to outsourcing, particularly those that can be performed remotely or do not require extensive localized knowledge, have seen a decline. Conversely, jobs that necessitate a physical presence or rely heavily on local market understanding tend to remain domestically anchored. This dynamic has put a spotlight on the need for workers in developed economies to adapt to the changing market, often requiring a shift toward more specialized, technical, or management-focused roles that are less susceptible to outsourcing.

Companies are not only outsourcing for economic reasons but also to capitalize on global expertise. As certain regions develop specializations in fields like IT, customer service, or manufacturing, companies may outsource to benefit from high-quality services while also reducing costs.

5.2.5 The Role of Vocational Training

Vocational training often provides specific skills directly tied to existing jobs in the economy. This training can lead to immediate employment upon completion, reflecting the lower unemployment rates observed for individuals with vocational qualifications. This suggests that vocational training may be more responsive to immediate labor market demands compared to traditional academic paths.

5.2.6 Policy and Economic Support Structures

Government policies and economic support structures also play a critical role in employment outcomes. Economic stimulus measures, job creation programs, and educational subsidies can all influence employment rates. Regions with proactive workforce development policies might show more robust employment figures, particularly for demographics that benefit most from such policies.

5.3 What could this entail for the future

As we interpret the results and consider their implications for the future, a central theme emerges the evolving landscape of employment in the face of advancing artificial intelligence (AI) and the globalization of the workforce. These dynamics present a dual challenge: on the one hand, the integration of AI into various sectors threatens to supplant jobs traditionally performed by humans; on the other, the trend of outsourcing work internationally poses its own set of challenges for domestic employment.

Companies are increasingly inclined to adopt AI technologies not only for their potential to cut costs and increase efficiency but also for their ability to perform tasks with precision and consistency that outmatches human capability in certain areas. This push towards automation is evident across a range of industries, from manufacturing and logistics to services and administration. The allure of AI lies in its promise of perpetual productivity without the inherent limitations of human labor, such as the need for rest, susceptibility to error, or demands for benefits and fair wages. There is now this push to "Learn AI now or risk losing your job, experts warn" (Hennessy (2023)).

Simultaneously, the global market offers opportunities for companies to outsource work to regions where labor costs are significantly lower, further exacerbating the displacement of jobs in higher-cost countries. This trend is facilitated by the digital age, which allows for seamless collaboration and communication across continents, making geographical boundaries less relevant to where and how work is performed.

These shifts necessitate a reevaluation of the role of human workers in an increasingly automated and globalized job market. The key for individuals is to cultivate skills and attributes that are less susceptible to replacement by AI or outsourcing. This includes:

- **Complex Problem-Solving**: Developing the ability to tackle intricate issues that require nuanced understanding and creative thinking, areas where AI still lags behind human capability.
- **Emotional Intelligence**: Enhancing skills related to emotional awareness, empathy, and interpersonal communication, which are crucial in professions such as healthcare, education, and customer service where human interaction is paramount.
- **Adaptability and Lifelong Learning**: Staying agile in the face of technological advancements by continuously updating one's skill set and embracing new knowledge areas, particularly those that are complementary to AI technologies.
- **Innovation and Creativity**: Leveraging innate human creativity to drive innovation, an area where AI can assist but not originate.
- **Physical Presence**: Jobs that require a physical presence as mentioned before are less likely to be replaced by AI. For instance, it is difficult for AI to replace people such as plumbers firefighters or people working in trades.

As we move forward, the interaction between human labor, AI, and the global workforce will shape the future of employment. Companies and individuals alike must navigate these waters with foresight, balancing the benefits of technological and global workforce integration with the need to maintain a vibrant, engaged, and skilled human workforce. The challenge lies not in resisting change but in adapting to it, ensuring that the workforce of the future is equipped to complement emerging technologies rather than be displaced by them.

5.4 Weaknesses and next steps

In evaluating the data and methodology utilized in our analysis, several weaknesses warrant attention, alongside considerations for future data collection efforts aimed at refining our understanding of the labor market dynamics.

One notable limitation is the potential for sampling bias inherent in survey-based data collection methods like the Labour Force Survey. Despite rigorous sampling techniques, certain segments of the population, such as transient workers or those in informal employment sectors, might be underrepresented, leading to gaps in the captured data. This underrepresentation could skew the unemployment rates and not fully reflect the nuances of the job market.

Furthermore, the data's reliance on self-reported information poses a challenge, as it may be subject to response bias. Individuals' interpretations of their employment status or educational level can vary, potentially leading to inconsistencies in the categorization and measurement of unemployment rates.

Additionally, the rapid pace of change in the modern economy, driven by factors such as technological advancements and globalization, means that data can quickly become outdated. The interval between data collection and publication, though relatively short, might not capture the most current labor market trends, especially in times of economic volatility.

To address these limitations and enhance the robustness of future data collection efforts, several steps can be taken:

- **Expanding Coverage**: Efforts should be made to include hard-to-reach populations and those in non-traditional employment arrangements to ensure a more comprehensive representation of the labor force.
- **Enhancing Data Collection Methods**: Incorporating a mix of quantitative and qualitative data collection methods could provide a more nuanced view of the labor market. This might involve detailed interviews, case studies, and the use of alternative data sources like social media analytics or real-time labor market data from online job platforms.
- **Leveraging Technology**: Adopting advanced data collection technologies, such as mobile surveys or web scraping techniques, can offer more timely and frequent labor market insights, enabling a near-real-time analysis of trends.
- **Cross-validation with Other Data Sources**: To ensure the reliability and accuracy of the data, cross-validation with other labor market studies and administrative records can help identify and rectify discrepancies or biases in the survey data.
- **Fostering International Collaboration**: As outsourcing and the global distribution of labor become increasingly prevalent, international collaboration in labor market research can provide a more holistic view of global employment trends, helping to contextualize domestic data within the broader global economy.

By addressing these weaknesses and adopting forward-looking data collection strategies, future research can provide deeper insights into the evolving labor market, ultimately informing more effective policy interventions and workforce development initiatives.

6 Conclusion

In conclusion, our exploration of unemployment rates across various educational levels and demographics, set against the backdrop of an evolving technological landscape and globalized economy, reveals intricate patterns and raises critical questions about the future of work. The data suggests that educational attainment plays a significant role in employment prospects, yet it is clear that the nature of education and the fields of study are pivotal in determining its true value in the job market. As artificial intelligence and automation become increasingly prevalent, the threat of job displacement looms large, not just for manual or routine jobs but also for roles traditionally considered secure within the realms of higher education.

The trend of outsourcing further complicates the employment narrative, presenting both challenges and opportunities as companies seek to leverage the global talent pool. This shift necessitates a reevaluation of domestic workforce strategies and underscores the importance of fostering skills that are resilient to these global trends, such as emotional intelligence, creativity, and adaptability.

As we stand at the cusp of significant shifts in the labor market, policymakers, educators, and individuals must engage in proactive dialogue and action. There is a pressing need to align educational programs with future job market demands, emphasizing not just technical skills but also the soft skills that distinguish human workers from AI. Moreover, lifelong learning must be integrated into career trajectories to ensure that the workforce remains adaptable to emerging technologies and industry shifts.

The journey ahead is complex and fraught with uncertainties, yet it also offers a canvas for innovation and adaptation. By embracing change and viewing it as an opportunity for growth, we can navigate the challenges of AI integration and globalization, ensuring a future where human labor complements technological advancements, leading to a more resilient and dynamic job market.

In essence, our findings call for a collective reimagining of the future of work, where education, policy, and workforce development converge to create a labor market that is inclusive, adaptive, and forward-looking. As we move forward, it is clear that the intersection of technology, education, and labor will continue to be a critical area of study, shaping the contours of our economic and social landscape in the years to come.

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