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Analysis of the Relationship between AI Advancement and Employment Dynamics in Canadian Higher Education

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The study focuses on the employment dynamics and higher education in Canada. AI technologies have been one of the most important drivers for employment growth, but it should be discussed whether AI advancements also increase the unemployment rate. Additionally, AI technologies are positively utilized by postsecondary education institutes, but whether the AI advancements can also impact the lower-income families on higher education remains discussed. This study primarily employs secondary data, leveraging existing datasets to evaluate four hypotheses. For the classification task, a Random Forest algorithm was selected as the main predictive modeling approach. Our results suggest that AI has slightly restricted access to higher education for low-income students, but is unlikely to have a significant contribution to job replacement within Canadian universities, and our results can be also used to explore longitudinal data on AI's impact on education and employment, assess how AI-driven policies shape long term workforce trends, and examine the ethical considerations surrounding AI deployment in academia.

Keywords: *artificial ıntelligence, higher education, employment in Canada, job replacement, low-income family*

Introduction

Employment trends serve as a crucial indicator of economic stability and growth. The integration of artificial intelligence (AI) into labor markets has introduced both opportunities and challenges. According to Damioli et al. (2024), AI technologies have emerged as significant drivers of employment growth, contributing to increased productivity and the creation of new job sectors. However, these optimistic projections contrast with recent labor market statistics. In 2024, the unemployment rate in Canada rose to 6.1%, marking a 0.3 percentage point increase from the previous year (Thanthong-Knight 2024). This discrepancy raises critical concerns regarding the nuanced effects of AI on employment dynamics, particularly the potential displacement of workers in certain industries.

Given these contrasting perspectives, a comprehensive analysis of AI's role in the Canadian labor market is necessary. This study aims to examine the overall impact of AI advancement on the structure and accessibility of higher education in Canada, with particular attention to its implications for equity, institutional dynamics, and employment outcomes. Rather than treating these

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issues independently, the study adopts an integrated perspective in which funding patterns, student accessibility, academic integrity, and employment dynamics are considered as interconnected dimensions of a broader systemic transformation driven by AI. The research will explore whether government-driven AI initiatives foster job creation or contribute to labor market disruptions, particularly within Canadian universities and research institutions.

Literature Review

AI's role in education has garnered significant scholarly attention, particularly in its potential to enhance learning accessibility. According to Osorio et al. (2024), AI-driven educational tools can accommodate diverse learning needs, providing personalized learning experiences that improve student engagement and academic outcomes. However, the socioeconomic implications of AI in higher education remain a subject of debate, particularly concerning whether AI-driven advancements equitably serve different income groups.

From a socioeconomic perspective, assessing whether AI benefits all students equally or exacerbates existing educational inequalities is crucial. One critical aspect of this discussion is the accessibility of higher education for low-income families. According to Innovation, Science and Economic Development Canada (2024), the national poverty rate stood at 9.9% in 2022, indicating that 3.8 million Canadians lived below the poverty line. This raises the question of whether AI-driven educational technologies provide meaningful opportunities for low-income students or if financial and digital access barriers limit their effectiveness. This study will investigate how AI influences post-secondary education accessibility, particularly for financially disadvantaged students. It will analyze whether AI-based education solutions, such as automated learning platforms, AI-assisted tutoring, and adaptive learning technologies, contribute to reducing or reinforcing disparities in higher education.

There are two foundational perspectives when discussing inequalities: inequality of outcome and opportunity (Danaher 2024). Jonathan et al. (2023) highlight that the advancement of AI has inadvertently perpetuated biased datasets, resulting in unequal outcomes such as exclusion, racism, and gender inequality, which can have adverse effects on human health. In addition, the advancement of AI tools also leads to inequality in opportunities, including accessibility to education, and resource allocation (Danaher 2024).

These inequalities mainly represent four biases, including model design rooted in feature selection, model training and predicting, model deploying, and model evaluating (Chung & Freedman 2024). For example, the feature may tend to high-income groups and jurisdictions rather than minority groups and regions. In addition, the model training and predicting biases are mainly from the skewed model training, including the biases of certain genders and economic groups, leading to unequal outcome predictions (Chung & Freedman 2024). Moreover, the model deploying biases mainly relates to accessibility (Chung & Freedman 2024). For example, the AI model may preferably be deployed in urban rather than rural areas. Finally, the model evaluating biases happens if the evaluation metrics are mainly for specific needs in different groups (Chung & Freedman 2024). For example, suppose the higher accuracy mainly shows the high-income groups and urban areas. In that case, the biases are generated because this evaluation metric is under consideration of the middle-class group, which also leads to poor performance.

Regarding the implications of AI-driven inequalities for higher education, biased datasets increasingly influence university admissions processes, as many institutions now rely on AI-based tools to evaluate and select candidates globally. The use of biased data can result in systematic mismatches between students and institutions, reinforcing existing inequalities within higher education systems (Austin et al. 2023). Furthermore, advancements in AI have shifted labor-market demand toward AI-related occupations, creating enhanced career opportunities for graduates with training in AI and related fields (Wong 2024). Conversely, this shift may reduce employment prospects for graduates from disciplines such as literature and other non-technical fields, thereby widening disparities across academic domains (Wong 2024).

Teaching is a profound learning experience, embodying the inherent connection between teaching and learning. With the advancement of AI, this connection can be deepened considerably and enhanced. AI can analyze learners' individual needs and tailor teaching strategies to cultivate their growth better (Jamie & Barry 2024). In addition, AI tools can greatly improve accessibility for learners with disabilities (Bressane et al. 2024).

However, the integration of AI in teaching and learning comes with its challenges. A study by Ivanov (2023), highlights that learners' overreliance on AI tools for completing assignments has compelled educators to re-evaluate their assessment methods, often diverting focus from developing personalized teaching strategies (Ivanov 2023). The excessive use of individualized teaching materials to meet learners' needs may also limit learners' exposure to course content, meaning that learners spend less time on exposure to topics (Ivanov 2023). Moreover, AI-based learning and teaching lack emotional and interpersonal interaction (Vistorte et al. 2024). Specifically, AI tools are unable to provide empathy, motivation, and inspiration, which can diminish the passion and energy of both learners and educators. Finally, an overreliance on AI tools can stifle creativity. Students may focus solely on finding ready-made answers rather than engaging in critical thinking, while instructors may only produce AI-generated content instead of thoughtfully designing materials tailored to students' needs (Habib et al. 2024).

Although AI tools can help researchers in higher education during the whole stage of the research process, these tools also mislead researchers to produce incorrect content, and the loss of research abilities for researchers gradually happens in the long run (Ivanov 2023). Additionally, applying AI tools in Academic Research forces research publications to launch stricter publication rules because academic research output may be recognized as not an intellectual contribution (Ivanov 2023).

Research evaluation also plays a vital role in educational practices. Compared to traditional research evaluations, including peer review, citation analysis, and institutional metrics, the research evaluations based on AI advancement mainly use AI tools, such as natural language processing, to optimize those three traditional research evaluations. Although AI tools increase the effectiveness of research evaluations, there is massive room for improvement in assessment because of insufficient, low-quality, and biased datasets due to inaccurate evaluations.

Moreover, AI models, such as natural language processing and machine learning algorithms, are widely used in the student admission process to higher education generating an effective and efficient administrative environment (Raman 2024). Specifically, machine learning models can significantly ease the decision-making process in university admissions. These predictive models can analyze historical data to help universities assess the likelihood of candidates successfully receiving offers. Finally, big AI models, such as Natural Language Processing (NLP), can help students navigate admission by reducing language barriers worldwide.

However, there are many concerns when proceeding with AI for student admissions, such as ethical considerations, student data privacy, and biases and fairness, impacting the decision-making process (Raman 2024). Specifically, the biases or discriminations in AI models exist if the previous admissions limited certain groups, including gender, race, jurisdiction, and so forth. In this case, equity, diversity, and inclusion cannot be ensured unless the admission policies require them. Finally, data privacy risks may exist when institutions misuse personal data or reduce the data transparency for their admission.

AI tools can enhance the efficiency of academic tasks performed by lecturers, including assessment, grading procedures, and reduction of the administrative burden, but AI algorithms can gradually achieve this work, which causes the job replacement of administrators and lecturers (Elizabeth 2024). Specifically, AI tools may replace certain administrative roles where job functions are highly repetitive, such as customer service tasks that can be automated through AI-powered chatbots. In addition, AI tools can perform document verification tasks more efficiently and accurately, reducing the need for manual administrative labor. Finally, instructors may face increasing concerns about job replacement as AI systems become more capable of delivering personalized content, providing feedback, and supporting student learning independently. In this case, AI advancements can provide tailored content and individual feedback for learners, which increases their learning efficiency. However, because students continue to value in-person interaction, mentorship, and discussion with professors, widespread job displacement in higher education is not rapidly happening. Nevertheless, concerns remain that AI tools may increasingly assume educational work that have traditionally been performed by academic staff (Elizabeth 2024).

Table 1 (Statista 2023a, b) presents a global overview of AI adoption across industries and functional areas. The findings indicate that, relative to other sectors, organizations in business, legal, and professional services primarily adopt AI for manufacturing and supply chain management. In the consumer goods and retail sector, AI is predominantly applied to human resources, service operations, strategy and corporate finance, and supply chain management. Within financial services, AI adoption is concentrated in product and service development, service operations, strategy, and corporate finance. In the healthcare and pharmaceutical sectors, AI is mainly utilized for human resources and risk management functions. Similarly, in high-technology and telecommunications industries, AI adoption is largely focused on risk management, service operations, strategy, and corporate finance.

Table 1. *AI Adoption Rate (%) Worldwide 2022 by Industry and Function (Statista 2023a, b)*

Characteristic	Human resources	Manufacturing	Marketing & sales	Product/service development
All industries	11	8	5	10
Business, legal, and professional services	11	10	9	8
Consumer goods/retail	14	4	3	4
Financial services	1	8	7	31
Healthcare/pharma	15	7	2	4
High tech/telecom	6	6	4	7
Characteristic Supply	Risk	Service operations	Strategy & corporate finance	chain management
All industries	19	19	21	9
Business, legal, and professional services	16	20	19	12
Consumer goods/retail	15	31	29	11
Financial services	17	24	23	2
Healthcare/pharma	22	12	8	8
High tech/telecom	38	21	25	8

Methodology

This study primarily employs the quantitative research methodology to explore the hypotheses we defined for this research and the correlation between the use of AI and higher education as well as employment dynamics in Canada. The feature selection process in this study was primarily theory-driven and constrained by the limited availability of longitudinal public datasets related to AI, higher education, and employment dynamics in Canada. Rather than relying solely on automated statistical feature selection techniques, variables were selected based on their conceptual relevance to the proposed hypotheses, consistency with the literature, policy significance, and availability of comparable annual observations across the study period. This approach is consistent with exploratory policy-oriented research, where interpretability and theoretical grounding are prioritized over predictive optimization. Consequently, the selected features should be interpreted as representative indicators of broader structural trends rather than exhaustive predictors of AI's societal impact.

A Machine-Learning based data research design is used to analyze and predict whether AI has a negative impact on higher education in Canada through eight relevant features, including funds allocation to AI by the Federal Government, fund allocation to education by the Federal Government, undergraduate tuition fees for Canadian citizens, number of students enrolled in post-secondary institutions, number of people with low income, number of cases of data violation due to AI in Education, number of studies on academic misconduct due to AI, and whether misuse of AI on academic dishonesty in Higher Education.

Analysis of Variance (ANOVA) was employed to test the statistical significance of differences in mean values across groups or relationships between variables corresponding to each hypothesis. ANOVA is appropriate in this study because the research aims to evaluate whether variations in key predictors (e.g., AI funding, income levels, tuition fees) are associated with statistically significant differences in outcome variables (e.g., employment dynamics, accessibility to education, enrolment levels).

Compared to simple correlation analysis, ANOVA enables formal hypothesis testing by partitioning total variance into explained and unexplained components, making it suitable for evaluating group-based and regression-based relationships within small-sample policy datasets.

Data Collection

Tables 2-3 show that the secondary data are mainly collected through Statistics Canada, Statista, and relative academic studies. The data supports the hypotheses and predictions and explores the correlation between AI and higher education as well as employment dynamics in Canada.

Table 2. *Hypothesis and Source of Data Collection*

Hypothesis	Definition	Source
1	Null:The Canadian Government has no financial allocations for AI technologies over 10 years. Alternative:The Canadian Government has increasingly allocated funds for AI technologies over 10 years.	Departments of Finance Canada, 2024, Innovation, Science, and Economic Development, 2024, 2022, 2021, Government of Canada, 2019
2	Null: The application of AI does not increase job replacement in Canadian Universities. Alternative: The application of AI increases job replacement in Canadian Universities.	StatCan 2023
3	Null: There is not limited accessibility to higher education for low-income families in Canada due to the emergence of AI. Alternative: There is limited accessibility to higher education for low-income families in Canada due to the emergence of AI.	Statistics Canada 2025
4	Null: Increasing higher education costs does not negatively affect students attending universities in Canada. Alternative: Increasing higher education costs negatively affects students attending universities in Canada.	StatCan 2024a, StaCan 2024b

Data Analysis

In this study, eight features were selected (as presented in Table 3), based on their strong correlation with the research hypotheses as well as their alignment with domain knowledge. The random forest is chosen as the key predictive method for this classification problem due to its capability to handle mixed numerical and categorical variables, and reducing the chance of overfitting (Tang & Ishwaran 2017). Moreover, bootstrap takes random subsets of data points from the training set due to reducing overfitting, creating diversity, and working with high dimensional data to improve generalization (Borislava 2021). Finally, K-fold cross-validation maximizes the use of limited data by allowing each observation to serve as both training and validation data, thereby improving model reliability and reducing the risk of overfitting (Krstajic et al. 2014).

Feature Selection Rationale

The selection of eight features for this study (as presented in Table 3) is based on their strong correlation with the research hypotheses as well as their alignment with domain knowledge. The inclusion of domain-specific variables is critical for ensuring the validity and reliability of predictive models, particularly in complex, policy-driven areas such as AI funding and its societal impact. For instance, when examining whether the Canadian federal government has increased its allocation of funds to AI over the past decade, it is essential to include the federal government's AI funding data as a primary feature. This variable directly reflects policy decisions and budgetary trends related to AI investment. Excluding such a feature would weaken the model's explanatory power and reduce the conclusions' accuracy.

Table 3. *Predictive Model features (Secondary Data)*

Year/ Features	2017	2018	2019	2020	2021	2022	2023	2024	2025
Federal Funds allocation to AI (Million)	125	230	795	1000	401.6	443	2570	2403 .5	2388.61
Federal Funds allocation to Education (Million)	3170. 3	3331. 4	3587. 1	3788. 7	4166. 6	4037. 7	4258. 5	4800	4844.67
Undergraduate tuition fees for Canadian citizens	6618	6822	6468	6580	6660	6871	7152	7360	7252.07
Enrolled students Number in Higher Education	21200 00	21600 00	21800 00	21700 00	21900 00	22000 00	N/A	N/A	2245428 .57
Number of people with low income	30080 22	30681 68	31350 86	31692 46	31860 55	32474 02	33284 21	N/A	3407956 .07
Number of cases of data violation due to AI in Education	N/A	N/A	N/A	42	125	100	173	N/A	210
Number of Studies on Academic Misconduct due to AI	75	65	100	35	N/A	N/A	N/A	N/A	25
Whether Misuse of AI on Academic Dishonesty in Higher Education	Yes	Yes	Yes	Yes	Yes	Yes	Yes	N/A	Yes
Whether AI Has a Negative Impact on Education	Yes	Yes	Yes	Yes	Yes	Yes	Yes	N/A	Yes

Similarly, in predicting whether AI will have a negative impact on higher education in 2025, domain knowledge dictates that variables such as the number of reported data violations caused by AI in educational settings and the frequency of AI misuse in academic dishonesty should be prioritized. These features are instrumental in capturing trends related to the ethical and security concerns surrounding AI implementation in higher education. By incorporating these factors, the study ensures that the predictive analysis is both comprehensive and grounded in empirical evidence.

Exploratory Data Analysis (EDA)

During the exploratory data analysis phase, several key variables emerged as highly correlated with the predictive target variable, notably whether misuse of AI in academic dishonesty in higher education demonstrated a significant association with the predicted outcome (see Table 4). These features exhibited strong predictive relevance when analyzing AI's impact on higher education from 2017 to 2024.

Table 4. *Feature Importance in Random Forest Model*

Feature	Feature Importance
Funds allocation to AI by Federal Government	-0.590022
Fund allocation to Education by Federal Government	-0.686978
Undergraduate tuition fees for Canadian citizens (CAD)	-0.719605
Number of students enrolled in postsecondary institutions (Millions)	0.654468
Number of people with graduate education certificate (college/university)	0.993843
Number of people with low income (bottom quantile)	0.996091
Number of cases of data violation due to AI in Education	0.323092
Global Number of Studies on Academic Misconduct due to AI	0.340879
Whether Misuse of AI on Academic Dishonesty in Higher Education	1.000000

Note: This table shows the ratio of importance of different features.

For example, historical data from 2017 suggests that AI had a negative impact on higher education, primarily due to increasing incidents of AI misuse in academic settings. The presence of these three features in the dataset provided strong predictive signals, supporting the hypothesis that AI-related ethical concerns in education have intensified over time.

The analysis was conducted using Google Colab. After loading and preprocessing the dataset, including the handling of missing values, the target variable was defined. The analytical framework then incorporated Bootstrap resampling, Random Forest classification, K-fold cross-validation, and target value prediction. The complete implementation code is provided in Appendix A. This analytical approach addresses common dataset limitations, including missing values and limited data availability, while also providing predictive results through established performance metrics.

Data Limitations and Model Selection

Despite the robustness of the selected features, the dataset is constrained by certain limitations. The descriptive data consists of only nine features and eight descriptive values, which restricts the breadth of insights that can be derived.

In addition to categorical data handling, missing values was addressed to prevent biases and inconsistencies in the analysis. This study's most commonly employed techniques for handling missing data are mean imputation for numerical variables and mode imputation for categorical variables. Using the mean for numerical data ensures that missing values are replaced with the average of the available data, which is computationally efficient and preserves the overall distribution of the dataset. Similarly, mode imputation is used for categorical variables, replacing missing values with the most frequently occurring category. This method minimizes the introduction of bias while maintaining the structural integrity of the dataset.

Given these data characteristics, the Random Forest algorithm is identified as the most suitable classification model for this predictive analysis. Random Forest is particularly advantageous for this study because it efficiently handles numerical and categorical data. Additionally, it is well-equipped to manage missing data and mitigate overfitting, which is a common challenge in predictive modeling (Tang & Ishwaran 2017). The algorithm's ensemble learning approach enhances model stability and generalizability, making it an appropriate choice for analyzing the complex relationships between AI policies, ethical concerns, and their subsequent impact on higher education.

Predictive Model Development

As established in the previous section, Random Forest serves as the primary predictive model for this study due to its robustness in handling both numerical and categorical variables, its ability to manage missing data, and its effectiveness in reducing overfitting. One of the key techniques used in Random Forest is bootstrap aggregation (bagging), which improves model generalizability by creating multiple subsets of the training data. Bootstrap sampling involves randomly selecting data points with replacements, allowing some data points to be selected multiple times while others may be excluded from a given subset (Borislava 2021).

Table 5. *Three Bootstrap Indices of the Trees in Random Forest*

Tree 1	Bootstrap Indices:	[4 0 1 2 3]
Tree 2	Bootstrap Indices:	[4 4 0 0 0]
Tree 3	Bootstrap Indices:	[1 0 0 1 1]

For instance, Table 5 illustrates three bootstrap indices generated during training. In one specific bootstrap sample, the dataset includes features such as funds allocated to AI by the federal government, the number of individuals with graduate education certificates, and funding allocated to education by the federal government. The repetition of certain features within the bootstrap sample reflects the nature of resampling with replacement, which enhances model's stability by ensuring diverse training subsets.

Cross-Validation Strategy

Cross-validation is employed as a model validation technique to maximize the utility of the available dataset. Given the imbalanced nature of the dataset, stratified K-Fold cross-validation is utilized to ensure that each fold maintains a similar distribution of the target variable, thereby preventing biased performance estimates (Krstajic et al. 2014). The model is configured with n_splits = 5, meaning the dataset is divided into five folds, each serving as a validation set once while the remaining four folds are used for training. This configuration provides a balance between computational efficiency and reliable performance estimation.

Increasing n_splits to 10 could improve the performance by providing more training iterations; however, this adjustment would also increase computational time. Therefore, the choice of n_splits = 5 represents a trade-off between model accuracy and computational efficiency. Additionally, a random_state value of 42 is set to ensure reproducibility of results, which is a standard practice in machine learning research to maintain consistency across multiple experiment runs.

After executing the Random Forest model for predictive analysis, the model's performance is evaluated using multiple statistical measures, including Bootstrap Mean Accuracy, Cross-Validation Mean Accuracy, and a classification report that assesses Precision, Recall, and the F1 score. These evaluation metrics comprehensively assess the model's predictive capabilities and reliability.

Model Performance Metrics

a. Bootstrap Mean Accuracy

The Bootstrap Mean Accuracy is recorded as 1.0, indicating that the model achieves an average accuracy of 100% when trained repeatedly using bootstrap sampling (See Table 6). This metric reflects the model's ability to maintain consistent predictive accuracy across multiple resampled training subsets.

b. Cross-Validation Mean Accuracy

The Cross-Validation Mean Accuracy is also 1.0 (See Table 6), signifying that the model achieves perfect accuracy when evaluated through cross-validation. This result suggests that the model performs consistently well across different validation folds, further reinforcing its predictive reliability.

Table 6. *Evaluation of the Predictive Model*

Bootstrap Mean Accuracy:	1.0		
Cross-Validation Mean Accuracy:	1.0		
Classification Report:	precision	recall	f1-score
	1.00	1.00	1.00

Note: This table shows Bootstrap Mean Accuracy, Cross-Validation Mean Accuracy, and Classification Report.

Classification Report: Precision, Recall, and F1 Score

Precision = 1.0 (See Table 6): This score indicates that the model does not produce any false positives, meaning that every instance classified as "Yes" is indeed correct.

Recall = 1.0 (See Table 6): A recall score of 1.0 suggests that there are no false negatives, ensuring that all actual "Yes" instances in the dataset are correctly identified.

F1 Score = 1.0 (See Table 6): The F1 score, representing the harmonic mean of precision and recall, is also 1.0, confirming that both precision and recall are perfectly balanced.

These results indicate that the Random Forest model performs flawless classification within the given dataset. However, while such results may initially appear to indicate a highly effective model, they also raise concerns regarding the model's generalizability to unseen data.

Potential Overfitting and its Implications

Despite the model's seemingly perfect performance, it exhibits signs of overfitting, meaning that it may be memorizing patterns in the training data rather than learning generalizable relationships. Overfitting occurs when a model performs exceptionally well on the training and validation data but may fail to maintain the same level of accuracy when applied to new, unseen data.

This study's primary cause of overfitting is the limited dataset size, which restricts the model's exposure to diverse patterns and variations. When training data is insufficient, the model may become overly sensitive to specific details in the dataset rather than developing a robust decision boundary that can generalize effectively. To mitigate overfitting, future iterations of the model could consider the following approaches:

- Expanding the dataset by incorporating additional data points to improve model robustness.
- Feature selection optimization to reduce complexity and prevent reliance on noise within the data.
- Regularization techniques such as pruning the decision trees within the Random Forest model.
- Hyperparameter tuning, including adjusting the number of estimators and tree depth to balance bias and variance.

Results

For Hypotheses 1 through 4, the results of the ANOVA tests indicate p-values of approximately 0.009618 (Table 7), 0.006998 (Table 8), and 0.000 (Tables 9-10), all of which are below the 0.05 significance threshold. Accordingly, the null hypotheses are rejected in favor of the corresponding alternative hypotheses.

Figure 1 shows that while funding for AI technologies has been inconsistent, federal allocations for postsecondary education have demonstrated a continuous upward trend over the study period. As depicted in Figure 2, Canada has a high AI occupational exposure and strong complementarity between AI and education. This suggests that AI integration in the sector is more collaborative than disruptive. The results suggest that AI functions primarily as a complementary technology rather than a substitute for human labor within the higher education sector, with limited evidence of short-term job displacement, based on the selected indicators. Figure 3 shows the correlation between the number of University graduates and household income highlighting that access to higher education remains somewhat limited for low-income families in Canada. This is evident from the lower ratio of university graduates to households in the lowest income quintile compared to higher-income groups. Figures 4-5 demonstrate that escalating higher-education costs are associated with reduced university participation in Canada. This relationship is reflected in the increasing ratio between average undergraduate tuition fees and post-secondary enrolment levels. Finally, Table 11 and Appendix A present the prediction results, indicating that AI is expected to have a negative impact on higher education in Canada in 2025. This anticipated decline is primarily attributed to concerns regarding data privacy breaches and the misuse of AI tools for academic dishonesty.

Table 7. *The ANOVA Test Result for Hypothesis 1*

ANOVA								
	df	SS	MS	F	Significance F			
Regression	1	78865372.30	78865372.30	12.45	0.009618576868			
Residual	7	44343588.95	6334798.42					
Total	8	123208961.30						
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95%	Upper 95%
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
Funds Allocation to AI (CAD Million)	2.34	0.66	3.53	0.00961857691	0.77	3.90	0.77	3.9

Table 8. *The ANOVA Test Result for Hypothesis 2*

ANOVA						
Source of Variation	SS	df	MS	F	P-value	F critical
Between Groups	6425.33	2	3212.67	39.5	0.006997793192	9.55
Within Groups	244	3	81.33			
Total	6669.33	5				

Table 9. *The ANOVA Test Result for Hypothesis 3*

ANOVA						
Source of Variation	SS	df	MS	F	P value	F critical
Between Groups	28108346045220.00	1	28108346045220.00	4816.65	0	4.75
Within Groups	70027902643.00	12	5835658554.00			
Total	28178373947863.00	13	5			

Table 10. *The ANOVA Test Result for Hypothesis 4*

ANOVA						
Source of Variation	SS	df	MS	F	P-value	F critical
Between Groups	322562247.10	1	322562247.10	870.33	0	4.20
Within Groups	10377341.91	2829	370619.35			
Total	332939589.00					

Figure 1. *The Impact of Canadian Federal Expenditures on AI and Postsecondary Education from 2017 to 2024*

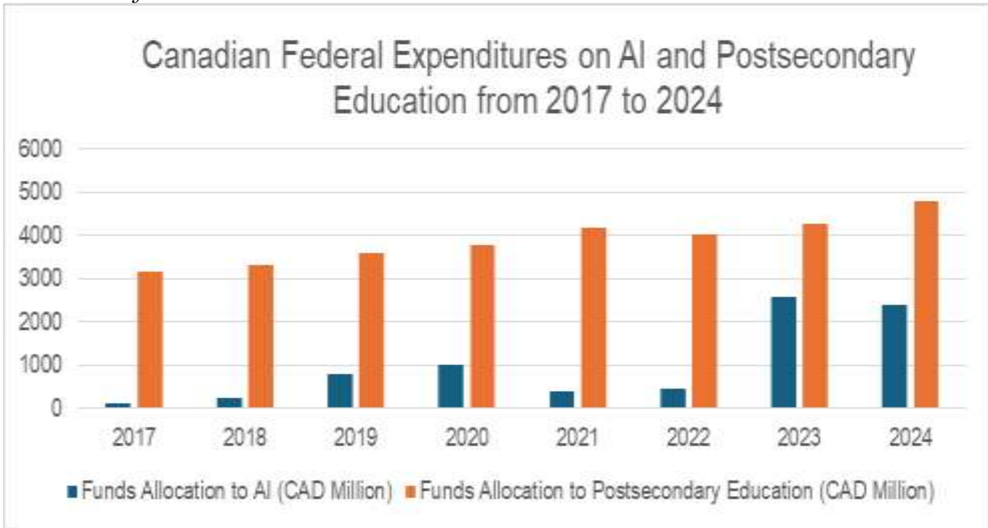

Figure 2. *Potential Artificial Intelligence Occupational Exposure and Complementarity across Occupations and Industries in Canada in 2021*

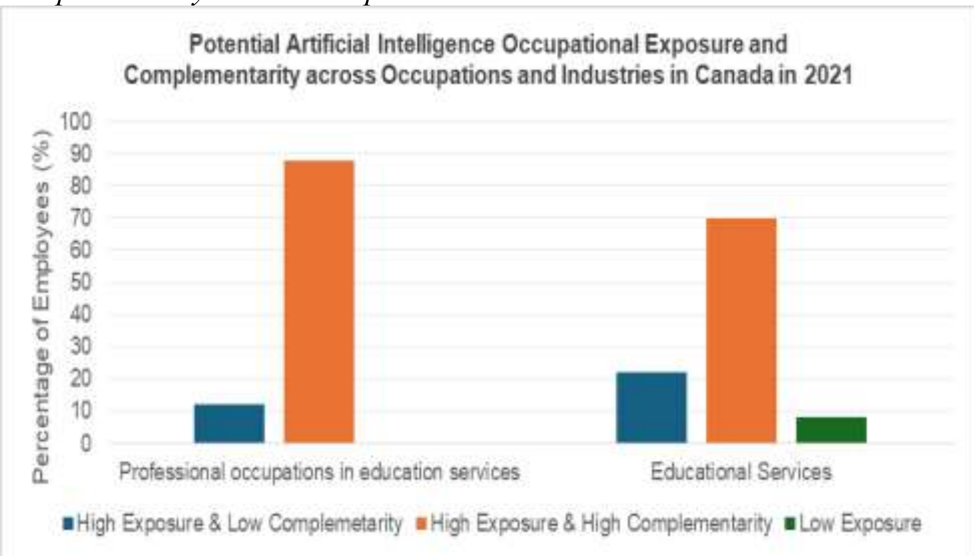

Figure 3. *The Number of University Graduates and Households in the Lowest Quintile in Canada from 2017 to 2023*

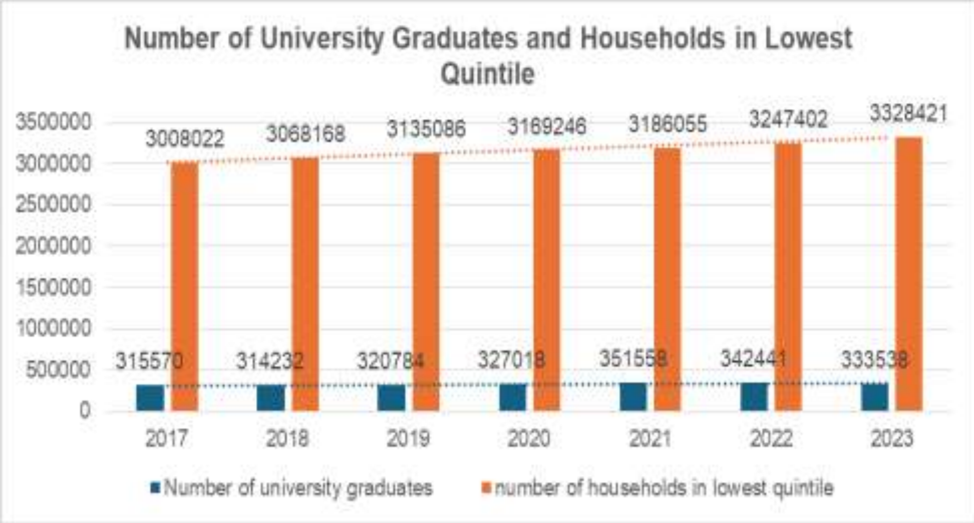

Figure 4. *The Average Undergraduate Tuition Fees for Canadian Citizens*

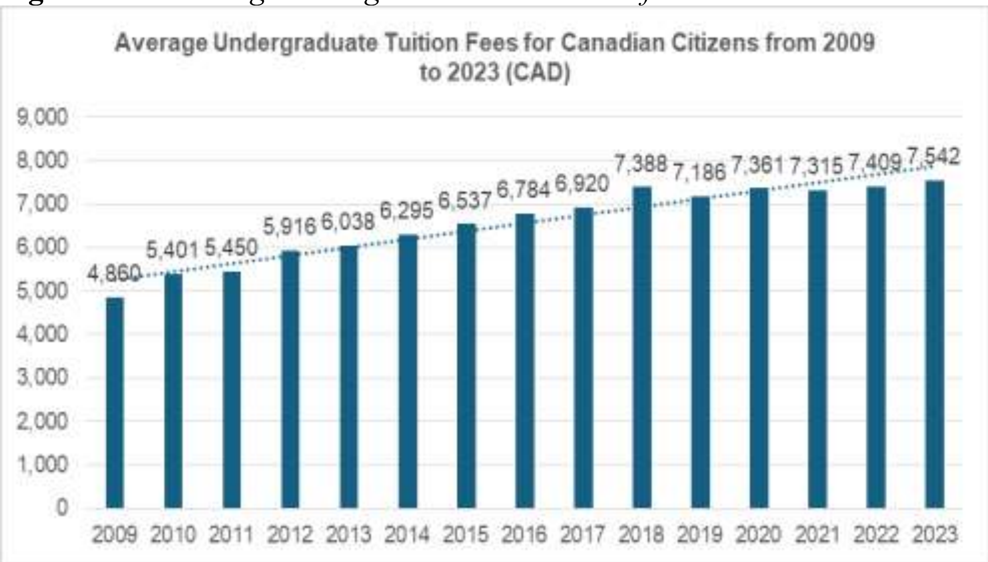

Figure 5. *The Number of Students Enrolled in Postsecondary Institutions in Canada from 2009 to 2023*

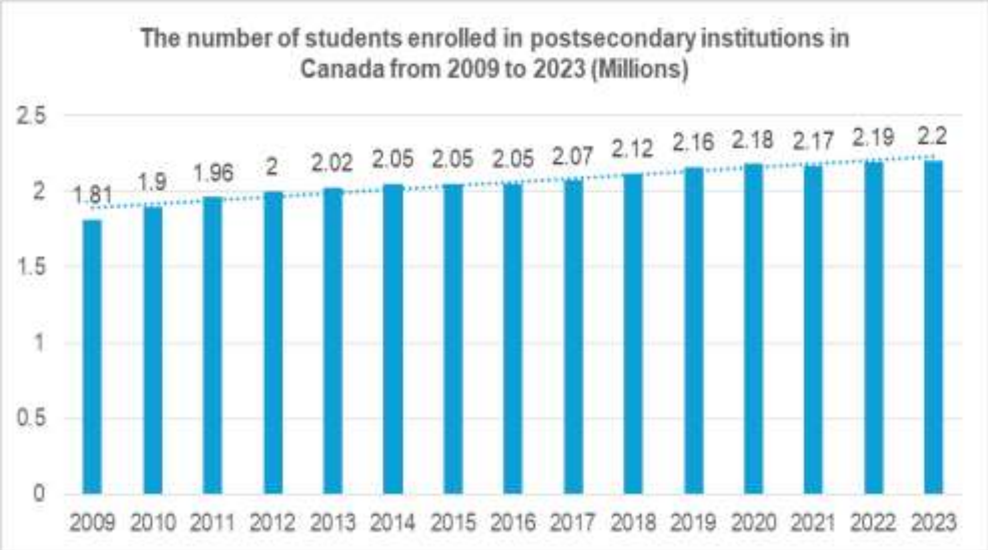

Table 11. *The Impact of AI Misuse on Academic Dishonesty in Higher Education*

Year	Whether AI is misused on Academic Dishonesty in Higher education or not
2017	Yes
2018	Yes
2019	Yes
2020	Yes
2021	Yes
2022	Yes
2023	Yes

Discussion

The findings of this study should be interpreted in light of several methodological limitations. Most notably, the analysis is based on a relatively small secondary dataset with limited temporal observations, which constrains the statistical power of both the ANOVA tests and the predictive model. In addition, the Random Forest model exhibited near-perfect accuracy, suggesting potential overfitting due to the limited sample size. As a result, the patterns identified in this study should be interpreted as exploratory rather than definitive.

In order to validate the hypothesis value, the ANOVA test was used if P-values are all less than 0.05, the results are proven to be significant.

The results of this study provide a nuanced understanding of the impact of AI on higher education accessibility, and employment dynamics in Canada. The findings suggest that AI may have introduced modest barriers to higher education accessibility for low-income families and may be associated with a slight deterrent effect on university enrolment, while simultaneously demonstrating greater complementarity than disruption within higher education employment in Canada.

Moreover, the study highlights a shifting trend in government funding priorities, particularly in the aftermath of the COVID-19 pandemic. During this period, the Canadian government has significantly increased its funds allocation toward AI development, often at the expense of direct funding for higher education institutions, which alleviates these significantly increasing requirements. This shift reflects broader national and global trends in technological investment, where AI is prioritized for its economic and strategic value. On the other hand, the gradual increase of funds from higher education infrastructure, research, and student support programs still requires Canada's post-secondary education system to consider long-term sustainability. Policymakers still need to carefully evaluate the trade-offs associated with AI investments to ensure that higher education institutions remain adequately funded and technologically equipped.

These findings are broadly consistent with recent literature on AI in higher education, while also adding a Canadian policy and employment perspective. For example, Osorio et al. (2024) and Sajja et al. (2024) emphasize that AI-supported learning systems can improve accessibility, personalization, and student engagement. However, the present study shows that these benefits may not be evenly distributed, as low-income families may still face barriers related to tuition costs, digital access, and broader socioeconomic inequality. This finding aligns with Danaher (2024), Chung and Freedman (2024), and Austin et al. (2023), who argue that AI systems can reproduce or deepen existing inequalities when biased data, unequal access, or uneven institutional deployment are not properly addressed.

The results also support the more cautious findings of Ivanov (2023), Habib et al. (2024), and Vistorte et al. (2024), who identify academic dishonesty, reduced creativity, emotional limitations, and ethical concerns as emerging risks of AI use in higher education. In this study, the predicted negative impact of AI on higher education in 2025 is similarly linked to academic misconduct and data-privacy concerns. At the same time, the employment-related findings are more consistent with Damioli et al. (2024) and Wong (2024), who suggest that AI does not simply eliminate jobs but reshapes labour demand and skill requirements. In the Canadian higher education context, the results indicate stronger AI complementarity than job substitution, suggesting that AI may support academic and administrative work rather than immediately replacing university employees. Therefore, this study extends the existing literature by showing that AI's effects in higher education are mixed: it may enhance efficiency and innovation, but it can also intensify equity, integrity, and governance challenges if not supported by inclusive funding and responsible institutional policies.

Conclusion

As shown in the results and findings, AI slightly limits the accessibility to higher education for low-income families and the increasing higher education cost negatively impacts students attending universities in Canada. Additionally, AI has a negative impact on higher education in Canada due to serious data violation and misuse of AI on academic dishonesty in higher education. Meanwhile, the Canadian government shows the upward trend for funds allocation for higher education, but funding for AI technologies has been inconsistent, particularly after COVID-19. On the other hand, advanced AI technologies result in concerns about employment, particularly job loss and job replacement in Canada, but these concerns are likely to be avoided in the higher education industry, which is a high AI occupational exposure and high complementarity in Education.

Nomenclature

Definition of Main Variables

Number of cases of data violation	The number of data misuse of students and employees' information (Statista 2023).
Number of Studies on Academic Misconduct	The number of data misleading academic researchers and students to generate incorrect content as a result of losing the research abilities in higher education (Ivanov 2023).
Binary variables related to AI misuse	The AI misuse mainly due to the use of biased data to result in mismatch between students and institutions and reinforce the inequality in higher education (Austin et al. 2023).

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Appendix A

The Detailed Code of Data Analysis can be accessed via the following link: https://github.com/AbbyGholidoust/Supplementary-Materials-for-Athens-Journal-of-Science/tree/main.