



Quantifying the Causal Impact of Employment Trends on Academic Performance Using Time-Series and Public Interest Data in Indonesia

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Abstract. This study quantifies the causal impact of employment trends on academic performance using a hybrid model of survey data and time-series public interest data from Google Trends in Indonesia. Employing Granger causality and regression analysis, the research investigates eight determinants of GPA and their relationship to labor indicators. A purposive sample of 40 respondents and secondary data from 2011–2019 were analyzed. Granger tests reveal significant one-way causality from employment to GPA indicators, particularly in parental monitoring ($F = 7.06$; $p < 0.05$) and learning motivation ($F = 9.68$; $p < 0.05$). Regression analysis supports these findings with R^2 values above 0.50. Results highlight the potential of integrating behavioral data into educational analytics. This research contributes methodological innovation by incorporating public interest data to explain academic outcomes, with implications for predictive modeling in education policy and planning.

Keywords: Causal Inference, CGPA, Google Trends, Granger Causality, Time-Series Analysis

(Received 2025-06-02, Revised 2025-07-31, Accepted 2025-07-17, Available Online by 2025-08-28)

1. Introduction

In the age of evidence-based decision-making, it remains a priority concern for policymakers and providers of post-secondary education to quantify academic performance and how it translates in terms of the workplace. Grade Point Average (GPA) has served as a uniform measure of student performance,

frequently applied by employers as a screening device during hiring. [1]. But the actual effect of GPA on labor market performance has become more debatable, as employers increasingly place more importance on soft skills, functional skills, and flexibility than on academic transcripts themselves [2]. Despite high GPAs, many graduates remain unemployed or working in non-correspondent employment. This mismatch indicates structural misalignment between education measurement and employment market uptake. Indonesia's Central Bureau of Statistics (BPS) statistics have reported that in February 2021, there were nearly one million unemployed university graduates, a figure which raises issues about the validity of GPA to be working [3].

Previous studies have explored this issue using survey-based and tracer study-based examinations constructed upon institutional or graduate-level data. While informative, such methodologies do not depict the broader societal views and temporal dynamics involved in GPA and labor market outcomes [4, 5]. Integrate traditional employment statistics with behavioral data extracted from Google Trends under a unified analytical framework [6]. This method is taken from an information system's perspective, in which public search behavior can be used as a proxy for society's interest and perception over time. Using time-series and causal inference techniques, this research strives to quantify the direction and magnitude of the correlation between employment indicators and determinants of GPA, such as parental supervision and motivation to learn [7, 8]. A model framework including behavioral analytics in educational impact analysis, showing the feasibility of using big data tools in supporting conventional educational evaluation systems.

The intent of this study is to develop and test a causal model to determine whether labor market trends influence educational performance metrics in quantifiable ways. Utilizing Granger causality testing and regression analysis, the study aims to bring an innovative perspective on how labor movements and public search activities intersect with the academic setting. The formation of hypothesis and model testing are intended not merely to answer scholarly inquiries but also to act as a guide for educational institutions and policymakers in addressing evolving needs in the world of work. The hypotheses are based on the causal linkages between employment indicators and eight determinants of GPA: environment, parental monitoring, financial, motivation to learn, study habits, time management, teaching quality, and student health. Both one-way and two-way causality for each determinant are examined with Granger tests, resulting in 24 statements of hypotheses.

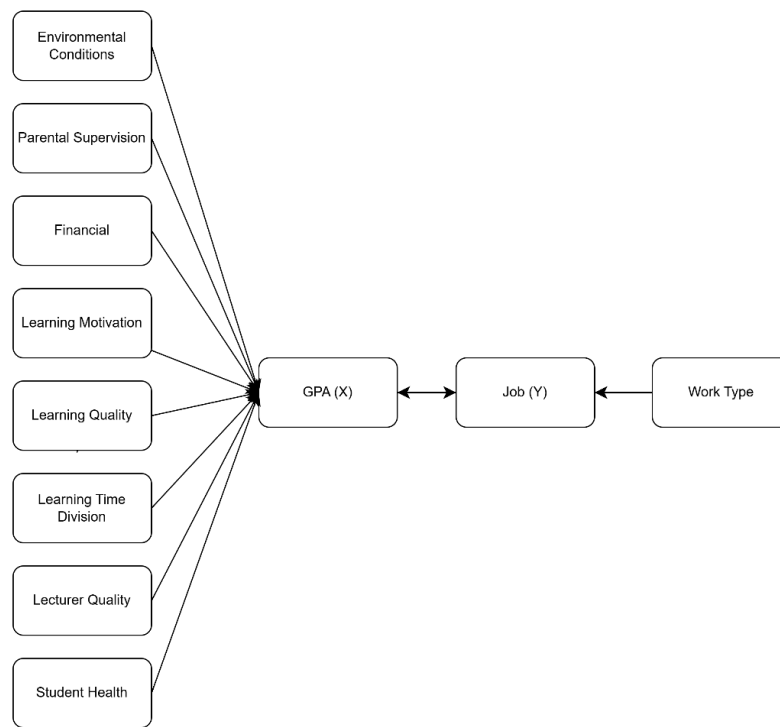
2. Methods

The current research employed a quantitative causal design to analyze the relationship between the Grade Point Average (GPA) and employment outcomes. A causal design was employed to determine if the relationship between the two variables was bidirectional, unidirectional, or non-existent and therefore enable predictive modelling [9, 10]. The population under study were individuals who had studied in institutions of higher learning. Purposive sampling was used to choose respondents who had some job-seeking experience after graduation. There were 40 respondents surveyed. Demographic information such as gender, level of education, and employment status was collected to characterize the sample. They are laid out in the Results. Two primary variables were compared in this study. The independent variable, GPA (X), was conceptually defined as the value of the average credit as a measure of a student's scholastic peak. It was operationalized by measuring eight dimensions: environmental conditions, parents' supervision, matters of money, learning motivation, learning quality, time management, excellence of teaching by lecturers, and students' health. The dependent variable, work (Y), was characterized as economic activities done to earn income for at least one hour continuously in the past week, measured by five indicators: residential area, skills obtained, education level, employment-seeking strategies, and occupation type [11].

Table 1. Operationalization of Variables

Variable	Concept	Indicator
GPA (X)	GPA is the average credit score that serves as the final grade unit reflecting the learning process or as a measure indicating the level of success achieved in the student's learning activities [12].	Environmental conditions, Parental Control, Financial, Motivation to learn, Learning Quality, Study Time Sharing, Quality of Lecturer Teaching, Student Health
Job (Y)	Work is an economic activity carried out by a person to help earn or earn income or profits with a length of working at least 1 hour in a row in the last week [3].	Residence, Skills, Level of education, Job Search Method, Type of Work

The research utilized a conceptual framework that combined technological, organizational, and human

**Figure 1.** Variable Modelling Diagram

factors. Specifically, the technological factor was the use of Google Trends as a data source, the organizational factor was keyword definitions and classifications, and the human factor was the public searching for keywords on GPA and work between 2011 and 2019. Data collection used primary and secondary sources. Primary data were obtained from a well-structured online questionnaire administered to respondents who had pursued higher education. The questionnaire was prepared with the help of a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Secondary data were gathered from Google Trends and Central Bureau of Statistics (BPS) over the period of 2011-2019. The frequency of predefined keywords concerning each GPA indicator was provided by Google Trends, while BPS offered the number of employments divided by the five indicators of the employment variable. When forming the research instrument, there was a systematic process followed. The items from the instrument were based on literature and expert perspectives and were conceptual framework

oriented. Validity and reliability of the instrument were tested with the application of IBM SPSS Statistics version 26. Those results are discussed below under the Results. Validity was established using correlation coefficients and the critical value of $r = 0.3$ being taken as the cut-off for success. Reliability was measured using Cronbach's Alpha, greater than 0.70 indicating good internal consistency [13, 14]. Keyword selection for Google Trends was subject to some guidelines to ensure it was correct and relevant. Keywords should be two-syllable Indonesian words in lower case, not abbreviated, and unique per indicator [15].

Table 2. Criteria and Keyword List

Keyword Criteria	Indicator	Keyword List
<ul style="list-style-type: none"> •Consists of two syllables •1 indicator = 1 keyword list • Indonesian •Lowercase words •Does not consist of abbreviations 	Environmental conditions	a place to learn
	Parental Control	time utilization
	Finance	financial education
	Learning Motivation	motivation to learn
	Learning Quality	instructional Media
	Study Time Management	carry out a task
	Lecturer Teaching Quality	learning methods
	Student Health	sleep pattern

Statistical methods used in the current study included descriptive statistics to create respondent profile summary and survey data summary, classical assumptions of testing (normality, linearity, and heteroscedasticity) for assessing the suitability of the model, and inferential analysis which included correlation and simple linear regression. Time-series analysis was also performed on the secondary data. The Augmented Dickey-Fuller (ADF) unit root test was used to test the stationarity of the time-series data. Variables that were identified as non-stationary at level were different until they were found to be stationary, enabling appropriate subsequent modeling [16, 17]. To test causality between employment measures and GPA, Granger causality tests were performed using EViews version 10 [18, 19]. The lag length for the Granger test was determined at two years as per annual data suggestions [20]. This process allowed the study to examine whether aspects of employment directly impact GPA trends over time, and vice versa. IBM SPSS Statistics version 26 and EViews version 10 software [21, 22] were used to perform all statistical analysis in this study.

3. Results and Discussion

3.1. Results

40 people participated in this research. 60% of the participants were male, and 40% of them were female. 92.5% of the participants were holding a bachelor's degree and 72.5% were still students at the time of data collection, as indicated in Table 3. This is a demographics section indicating that the participants were predominantly young adults who had some college-level education.

Table 3. Respondent Characteristic

Characteristic	Frequency	Percentage
Gender		
Male	24	60%
Female	16	40%
Education		
Undergraduate	3	7,5%
Bachelor's degree	37	92,5%
Occupation		
Not Working	4	10%
Student	29	72,5%
Private Employee	4	10%
Entrepreneur	1	2,5%
Others	2	5%

Descriptive analysis was applied to summarize the perception of the respondents towards the determinants of GPA and employment. For the GPA variable, the total of the respondents' replies amounted to 1,725 from 2,200 with the level of agreement being 78.40%. It indicates that parental supervision, financial support, and learning motivation are perceived to have significant determinants of GPA. Summary of the respondents' responses for the GPA variables is presented in Table 4 and graphically represented in Figure 2.

Table 4. Respondents' Responses Regarding GPA

Question Items	Response Frequency					Amount	Actual Score Index
	SD	D	US	A	SA		
1	0	0	7	16	17	40	170
2	0	1	8	17	14	40	164
3	1	2	6	17	14	40	161
4	0	3	7	12	18	40	165
5	0	1	5	18	16	40	169
6	1	1	5	19	14	40	164
7	0	2	6	19	13	40	163
8	1	2	9	18	10	40	154
9	0	3	12	17	8	40	150
10	1	3	16	14	6	40	141
11	5	6	14	10	5	40	124
Total Score Achieved						1.725	

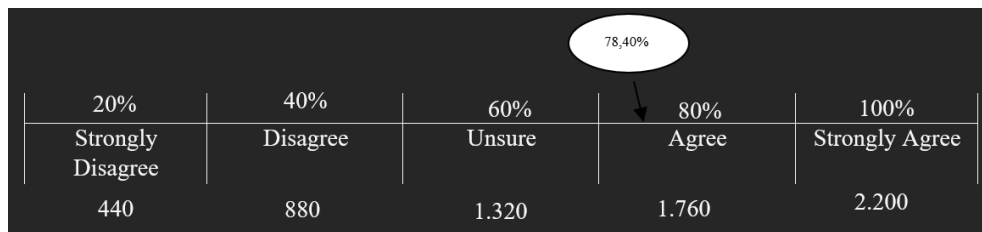


Figure 2. Continuous Line Variable X (GPA)

Similarly, in the employment variable, the total score was 788 from a total of 1,000 potential, which translates to 78.80%, which reflects that respondents perceived skills, education level, and work type as significant factors for securing employment. The breakdown answers of the employment variables are presented in Table 5 and illustrated in Figure 3.

Table 5. Respondents' Responses Regarding Work							
Question Items	Response Frequency					Amount	Actual Score Index
	SD	D	US	A	SA		
1	2	5	11	10	12	40	145
2	0	1	2	14	23	40	179
3	0	3	10	14	13	40	157
4	0	2	10	18	10	40	156
5	1	3	11	14	11	40	151
Total Score Achieved							788

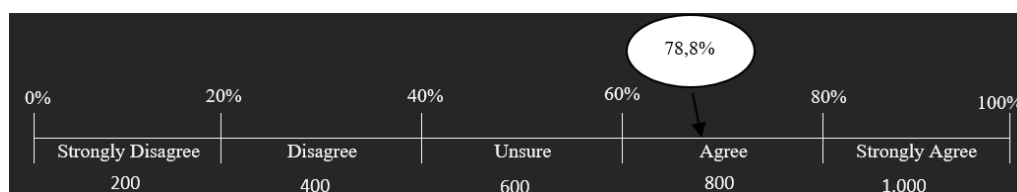


Figure 3. Continuum Line Variable Y (Job)

Instrument test confirmed that the questionnaire items were valid. The validity test results showed that all items for the GPA variable produced R-values greater than 0.3, from 0.494 to 0.794.

Table 6. GPA Variable Validity Test Results

Instrument	r-count	r-critical	Information
Statement X.1	0,668	0,3	Valid
Statement X.2	0,773	0,3	Valid
Statement X.3	0,606	0,3	Valid
Statement X.4	0,734	0,3	Valid
Statement X.5	0,794	0,3	Valid
Statement X.6	0,792	0,3	Valid
Statement X.7	0,780	0,3	Valid
Statement X.8	0,693	0,3	Valid
Statement X.9	0,494	0,3	Valid
Statement X.10	0,610	0,3	Valid
Statement X.11	0,641	0,3	Valid

Likewise, all items of the employment variable produced R-values greater than 0.3 were valid.

Table 7. Work Variable Validity Test Results

Instrument	r-count	r-critical	Information
Statement Y.1	0,809	0,3	Valid
Statement Y.2	0,617	0,3	Valid
Statement Y.3	0,694	0,3	Valid
Statement Y.4	0,751	0,3	Valid
Statement Y.5	0,811	0,3	Valid

Cronbach's Alpha reliability testing yielded 0.884 for GPA variables and 0.789 for employment variables, which were both above the 0.70 cutoff to ensure the internal consistency of the research instrument [23].

Table 8. Reliability Test Results

Variable	Cronbach's Alpha	Reliability Limit	Information
GPA	0,884	0,70	Reliable
Job	0,789	0,70	Reliable

Classical assumption tests were conducted to ensure data satisfied the requirements for inferential analysis. Normality test, shown in Figure 4, revealed that residuals followed along the diagonal line, and thus data were normally distributed.

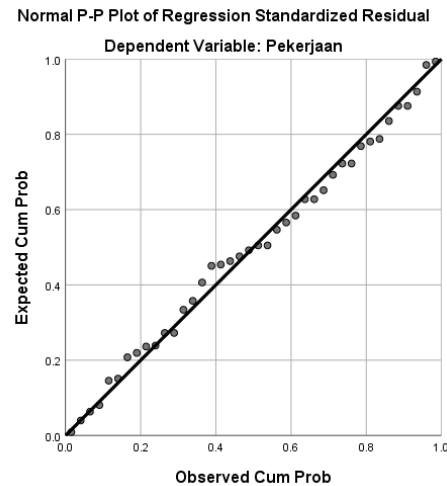


Figure 4. P-Plot Normality Graph

The linearity test produced a deviation from linearity significance value of 0.332 (> 0.05), confirming that there is a linear relationship between GPA and employment variables, as shown in Table 9.

Table 9. Linearity Test Results
ANOVA Table

			Sum of Squares	df	Mean Square	F	Sig.
Job*GPA	Between Groups	(Combined)	323.733	18	17.985	2.351	.031
		Linearity	165.577	1	165.577	21.642	.000
		Deviation from Linearity	158.156	17	9.303	1.216	.332
	Within Groups		160.667	21	7.651		
	Total		484.400	39			

The heteroscedasticity test results presented no visible pattern in the scatterplot, which is an indication of homoscedasticity [24, 25].

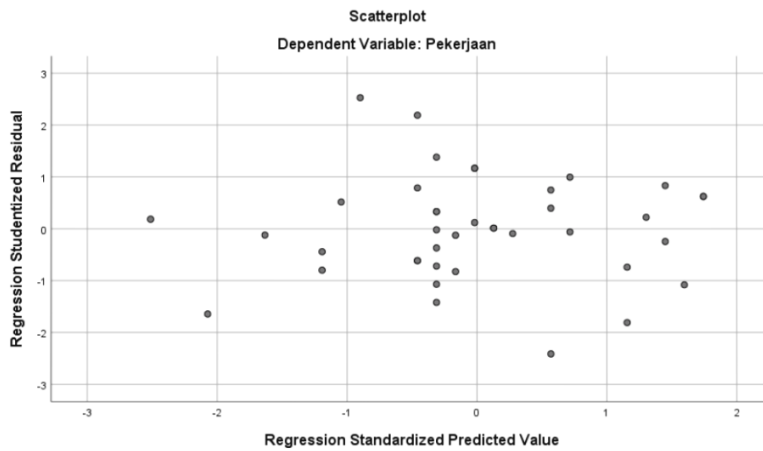


Figure 5. Scatterplot for Heteroskedasticity Test

For secondary analysis, time-series plots between the years 2011 and 2019 were generated to track trends in Google Trends search frequencies and employment rates. The plots demonstrated various data behaviors, including horizontal behavior in Figure 6, cyclical behavior in Figure 7, and trend behavior in Figure 8. Tabulated time-series data are presented in Table 10.

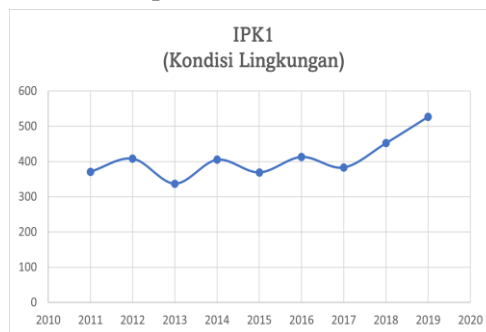


Figure 6. Time Series Plot (Horizontal Pattern)

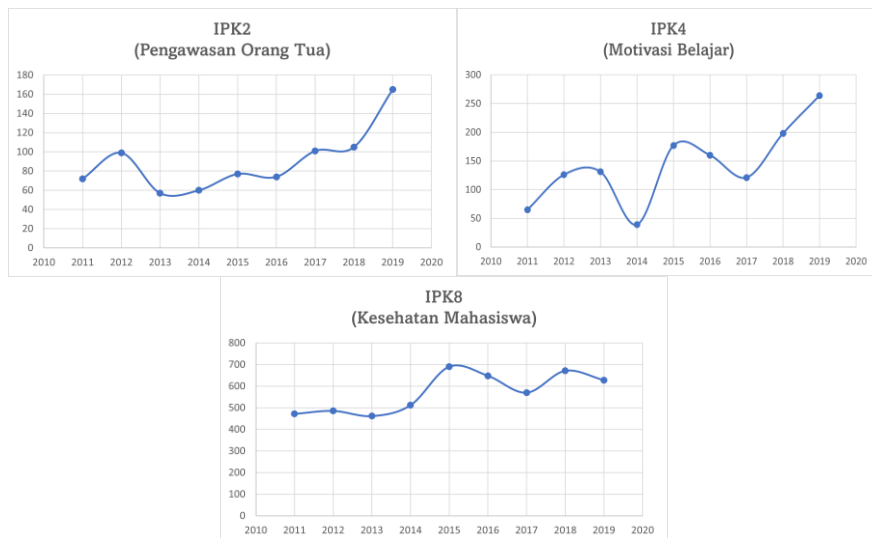


Figure 7. Time Series Plot (Siklikal Pattern)

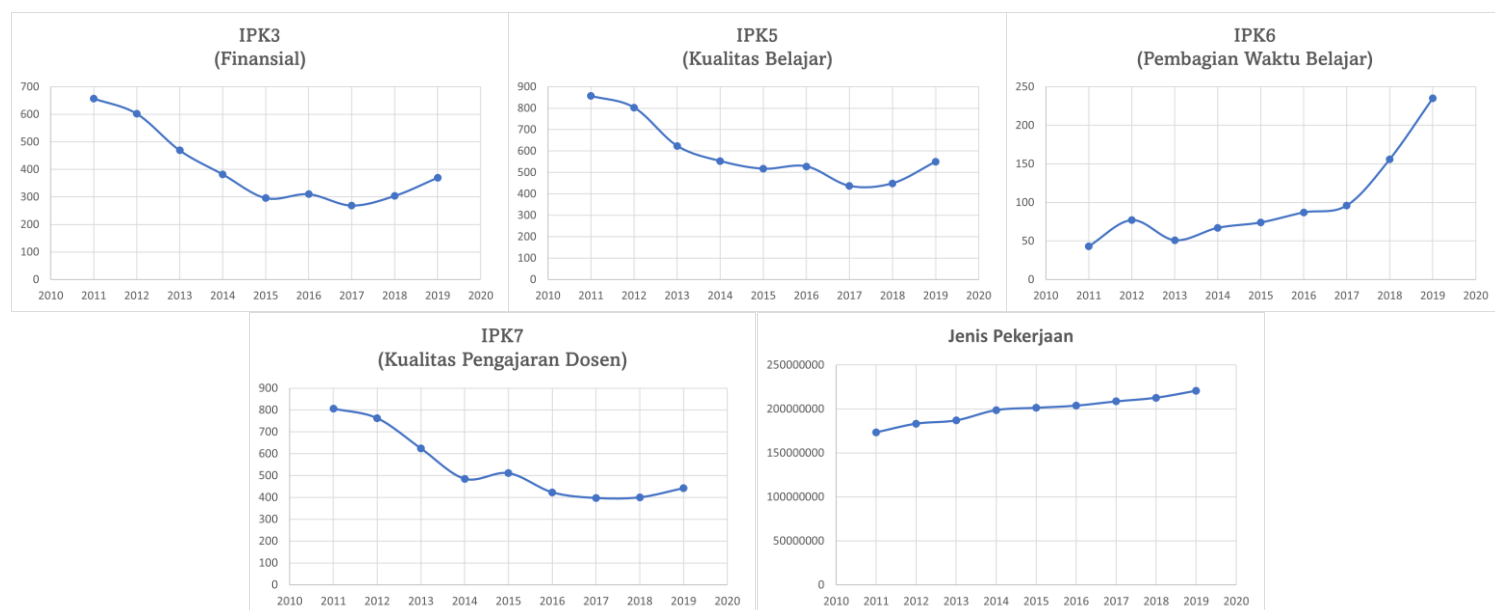


Figure 8. Time Series Plot (Trend Pattern)

Table 10. Data Tabulation

Years	Variable Indicator								
	GPA1	GPA2	GPA3	GPA4	GPA5	GPA6	GPA7	GPA8	Work
2011	371	72	675	65	857	43	807	472	68303702
2012	408	99	602	126	803	77	763	486	70274396
2013	337	57	469	131	624	51	624	462	70767036
2014	405	60	382	39	553	67	485	512	74369332
2015	369	77	296	177	517	74	511	690	76499370
2016	413	74	310	160	528	87	423	648	78308480
2017	383	101	269	121	437	96	397	570	84200909
2018	452	105	304	198	449	156	400	671	85033755
2019	527	165	370	264	550	235	442	628	89159278

Augmented Dickey-Fuller (ADF) test for unit roots was employed to check the stationarity of time-series variables. The results, presented in Table 11, indicated that all the variables were non-stationary at level because all the p-values were more than 0.05. After differencing, stationarity was achieved for most of the variables at either first difference or second difference.

Table 11. Unit Root Test Result

Variable Indicator	P-Value Level	P-Value First Difference	P-Value Two Difference
GPA1	0,9976	0,0279*	0,0002*
GPA2	0,9263	0,1567	0,0471*
GPA3	0,1530	0,9505	0,0069*
GPA4	0,5035	0,0246*	0,0127*
GPA5	0,1792	0,6401	0,0365*
GPA6	1,0000	0,9856	0,0096*
GPA7	0,2421	0,3888	0,0128*
GPA8	0,4831	0,1153	0,0464*
Work Type	0,9920	0,0235*	0,0000*

Granger causality was examined at a lag of two years to detect directional relationships between the employment variable and each of the GPA indicators. The results, as presented in Table 12, reflected robust one-way causality from work type towards parental supervision (GPA2) and motivation to learn (GPA4). Specifically, the F-statistic for work type that impacted GPA2 was 7.06417 and for GPA4 was 9.67857, which both exceeded the critical value of 5.59144785 at the 5% significance level. Causality was not detected in the reverse direction.

Table 12. Granger Causality Test Result

Null Hypothesis	F-Statistic
Environmental conditions	
JOB does not Granger Cause GPA1	2,03180
GPA1 does not Granger Cause JOB	0,99778
Parental Control	
JOB does not Granger Cause GPA2	7,06417*
GPA2 does not Granger Cause JOB	1,00515
Financial	
JOB does not Granger Cause GPA3	3,88760
GPA3 does not Granger Cause JOB	1,01122
Motivation to learn	
JOB does not Granger Cause GPA4	9,67857*
GPA4 does not Granger Cause JOB	2,40513
Learning Quality	

Null Hypothesis	F-Statistic
JOB does not Granger Cause GPA5	0,41503
GPA5 does not Granger Cause JOB	0,40559
Study Time Sharing	
JOB does not Granger Cause GPA6	0,80754
GPA6 does not Granger Cause JOB	0,59186
Lecturer Teaching Quality	
JOB does not Granger Cause GPA7	0,24134
GPA7 does not Granger Cause JOB	2,87050
Student Health	
JOB does not Granger Cause GPA8	2,00217
GPA8 does not Granger Cause JOB	0,96980

Further examination with simple linear regression placed a value on the influence of work type on the substantial GPA measures. For parental supervision (GPA2) in Table 13, the regression coefficient was 3.428×10^{-6} and significant at $p = 0.018$.

Table 13. Results of the Job Type Regression Model on GPA2

Coefficients ^a					
Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
1 (Constant)	-175.435	86.363		-2.031	.082
1 Job	3.428E-6	.000	.759	3.086	.018

a. Dependent Variable: GPA2

The obtained regression equation is:

$$Y = -175.435 + 3.428 \times 10^{-6} \times X \quad (1)$$

where Y denotes the GPA indicator and X represents the employment data.

For learning motivation (GPA4), the regression analysis yielded a coefficient of 6.735×10^{-6} at $p = 0.026$, which is shown in Table 14.

Table 14. Results of the Job Type Regression Model on GPA4

Coefficients ^a					
Model	Unstandardized Coefficients		Standardized Coefficients		Sig.
	B	Std. Error	Beta	t	
1 (Constant)	-379.176	186.509		-2.033	.082
Job	6.735E-6	.000	.728	2.807	.026

a. Dependent Variable: GPA4

The regression equation for this relationship is:

$$Y = -379.176 + 6.735 \times 10^{-6} \times X \quad (2)$$

These results are predictive of an increase in employment data for heightened trends in GPA regarding parental monitoring and motivation to study. In general, the findings confirm the proposed conceptual model, where certain employment variables, particularly the type of work, have significant positive effects on certain dimensions of GPA.

3.2. Discussion

This study provides proof that employment type traits in labor market patterns do exert a measurable effect on some indicators of student academic performance. Unidirectional causality is marked by high Granger causality from work to GPA measures such as parental monitoring (GPA2) and interest in learning (GPA4), where labor market patterns shift prior and can thus influence student orientation towards academic performance. Such findings are accompanied by statistically significant regression coefficients and p-values below 0.05. The use of Google Trends as a proxy for public interest is a methodological improvement in educational analytics. They might be giving us the views of the society and forces it has behind the learning context with sophisticated interpretation of behavior measures. But Google Trends are bound by disparities in access to the internet, possible noise in keyword searches and no resolution at the user level. Despite the above limitations, integration of behavioral and mainstream datasets to enhance the predictive quality of education models is evident in the research. Results from the current study are in line with findings of previous research highlighting the role of external socioeconomic inputs to achievement. Unlike common survey-research designs, the current analysis features a time-series design that preserves the time sequence and lag effects between labor measurements and GPA scores. The time aspect is usually omitted from static regression models applied in educational studies. From data science and engineering, the article provides the potential of using causal inference techniques to construct forecasting systems. The causality relationships established can be employed for constructing warning systems for academic risk based on timely signals from the labor market. Future work can include more high-grained data, machine learning techniques, or algorithmic adjustments for the purposes of higher generalizability and automatization. Overall, this study bridges the distance between education practice and external economic measures in a data-analytical framework. It confirms that socioeconomically significant correlations among work not only occur but can even be measured and predicted to advise education policy. Multi-disciplinary analysis models being taken on by policymakers have potential to be of real value in making data-driven interventions in schools.

4. Conclusion

This study corroborates that some work variables most significantly exhibit statistically significant one-way causality on some measures of academic performance, specifically parental supervision and study motivation. Granger causality tests yielded F-statistics of 7.06 and 9.68 respectively ($p < 0.05$), backed

up by regression analyses with $R^2 > 0.50$. The results point towards the potential impact of macro-level work indicators on micro-level academic behavior. The integration of Google Trends public interest data and time-series employment data adds new context to educational performance analysis as seen from the perspective of causal inference. While GPA remains a pertinent academic metric, the volatility of GPA is demonstrated to be commensurate with aggregate employment trends. The finding has implications for data-driven academic support system design and labor-sensitive curriculum design. Future studies will have to extend this model with greater, more representative samples, machine learning algorithms, and analysis of real-time labor data in conjunction with increased predictive validity. This research provides a replicable analytics model that can be applied to shape education policy, career readiness initiatives, and the enactment of early intervention mechanisms in colleges and universities.

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