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Editorial Note

The May 2025 issue of the *Journal of International Business Disciplines (JIBD)* has been the result of a rigorous process of blind reviews, and in the end, the reviewers recommended three articles for publication in this issue of *JIBD*.

JIBD is committed to maintaining high standard of quality in all of its publications.

Ahmad Tootoonchi, Chief Editor
Journal of International Business Disciplines

LONG-TERM AND SHORT-TERM RELATIONSHIPS BETWEEN THE US STOCK MARKET AND MACROECONOMIC VARIABLES: AN EMPIRICAL STUDY

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ABSTRACT

From an economic perspective, it is of interest to determine if two non-stationary economic time series are co-integrated. Two non-stationary series are co-integrated if a linear combination of the two series is long-term stationary. In this study, we test for co-integration and long-term relationships between macroeconomic variables, including the Dow and S&P 500, using the Johansen co-integration test and the vector error correction model, VECM. Also, we investigate short -term relationships between these variables, using the Granger test and VECM.

Results show that GDP is co-integrated with Dow, S&P 500 (SP), savings deposits, CPI, and debt. Also, Dow is co-integrated with SP, savings deposits, and debt. The SP index is co-integrated with debt, savings deposits, and CPI. Estimates of the long-term relationships between variables and rates of error adjustments are presented. Also, short-term relationships, from the Granger test and the VECM analysis are presented and compared.

INTRODUCTION

The stock market and the GDP play an important role in a country's economic and industrial growth. The long-term relationships, or equilibrium links, between stock market indexes and macroeconomic variables, are of importance to the economy of a country and to investment in financial markets. A long-term relationship, or co-integration, between stock market indexes and macroeconomic variables, can aid in predicting the behavior of an index according to the behavior of a macroeconomic variable since the two variables have a common trend in the long run. The interest in looking for common characteristics of two series, from which one can draw conclusions about their behaviors, leads to the concept of co-integration between the two series. From the point of view of economics, two series are co-integrated if they move together over time and the linear combination between them is stationary or stable. Hence, the two series have a long-term equilibrium towards which the economic system converges over time.

Relationships between economic time series can vary from country to country and from one time-period to another. Most of the studies on co-integration between macroeconomic variables are done in developing markets and little recent work is done on co-integration between economic variables in the US. Due to the relative lack of empirical studies on the long-term relations between economic variables, we investigate in this paper the long-term or equilibrium relationships between the Dow index, S&P index, the GDP, and macroeconomic variables using the Johansen co-integration test and the vector error correction model (VECM).

LITERATURE REVIEW

Hacker and Hatemi (2003) investigated in one set of variables, the co-integration of Swedish real exports, real GDP, and foreign real GDP. Also, they considered, in another set, the co-integration of Swedish real exports, total factor productivity, and foreign real GDP. Foreign real GDP was estimated as the total OECD real GDP minus Sweden's real GDP. Using the Johansen multivariate co-integration tests (trace and eigenvalue tests), the authors showed that the three variables within each set were co-integrated. There was only one co-integration vector in both sets. The Granger causality test showed that there was a bi-directional causality between real GDP and real exports and between real GDP and total factor productivity. Also, foreign real GDP Granger-caused real exports.

Markellos (1999) used co-integration to evaluate the performance of an investment strategy. The author argued that for an investment strategy to be successful, its cumulative returns over time should outperform the market cumulative returns and the two series should not be co-integrated. This is so since co-integration means that investment returns are tied to the market returns.

The author applied this co-integration test to evaluate various investment rules using the DJIA and the FT30 index on the London Stock Exchange. It should be remarked that cumulative returns of an investment strategy can be co-integrated with the market returns and still outperform the market. However, in this case, the difference between the investment returns and the market returns are positive but stationary over time, since the two series are co-integrated. In this case, although the investment strategy is still successful, it cannot break away from the market.

Ratanapakorn and Sharma (2007) investigated the long-term relationship between the S&P 500, stock price index, and six macroeconomic variables over the period 1975-1999. The authors applied the multivariate Johansen co-integration tests to determine the equilibrium or long-term relationships between variables. They reported that the S&P 500 price index was negatively related to the long- term interest rate but positively related to the money supply (M1), industrial production, inflation, the exchange rate, and the short-term interest rate.

Kaufmann (2004) applied a multivariate co-integration analysis of the vector error correction model (VECM) to determine the equilibrium relationships between heat measure of total energy use and types of fuels consumed (oil, gas, hydro, and nuclear), personal energy consumption expenditures, GDP, and energy prices. Four equilibrium vectors were identified based on the Johansen co-integration trace and eigenvalue tests. The first equilibrium or long-term relationship was between energy and personal consumption. The second long-term relationship was between energy and types of fuels consumed. The third long term relationship was between energy prices and energy use. The fourth long-term relationship was between energy use and price changes, GDP, and fraction of total energy consumption from oil and gas. These results indicated that energy use in the long run was associated with oil, gas and hydro and nuclear electricity. However, the model did not include coal under type of fuel consumed

Serfling and Miljkovic (2011) used co-integration analysis and the vector error correction model (VECM) to investigate the relationship between macroeconomic variables. The VECM model included the change in the dividend yield, the change in the yield on the 10-year Treasury note, the percentage change in the price level of the S&P 500 Index, the percentage change in the M1 money supply, interest rate, the percentage change in the industrial production index (IPI), and the percentage change in the CPI Results from the VECM analysis showed that change in dividend yield was affected by interest rate, money supply, and CPI. Change in yield on the treasury note was affected by dividend yield, interest rate, S&P 500 price, IPI, and CPI. Change in the S&P 500 price was affected by interest rate, money supply, IPI, and CPI. Current change in the money supply was affected by change in dividend yield, S&P 500, and CPI. Current change in the IPI was affected by interest rate and S&P 500. Change in CPI was affected by dividend yield, interest rate, S&P 500, and money supply. As such, the results showed feedback between variables.

Seabra (2001) investigated, using the Johansen co-integration test and the vector error correction model (VECM), the long-term relationships between the Argentine Merval, Brazilian Ibovespa, Japanese Nikkei, and US Dow Jones stock markets. Results showed that the Argentine and Brazilian stock markets were co-integrated with the US Dow Jones Industrial average. There was no co-integration between the other markets. Short-term results from the VECM indicated a stronger relationship between the Brazilian and Dow indexes than between the Dow and the Argentine stock market index.

Sahoo and Sahoo (2019) investigated the long-term relationship between unemployment rate in India and GDP, consumer price index (CPI), literacy rate, labor force, and domestic private investment formation. The data were over the period 1991-2017. The Johansen co-integration test and the VECM were used to study the co-integration and the long-term relationship between unemployment and the other variables. The co-integration test showed that long-term relationships existed among all the variables. The VECM results showed that unemployment was predictable by the explanatory variables in the model. The Granger test showed that GDP caused unemployment. There was a bi-directional causality between labor force and unemployment. Also, private investment, and labor force caused unemployment.

Maghrebi et. al. (2018) investigated the long-term and causal relationships between crude oil price and the GDP in Saudi Arabia, over the period 1998-2014. The Johansen co-integration analysis showed that crude oil price and GDP were co-integrated. Also, the Granger test indicated that there was a bi-directional relationship between crude oil price and GDP.

Huat and Wai (2009) studied the co-integration and causality between money supply (M1, M2, and M3) and GDP in Singapore. Data were quarterly over the period 1975 to 1998. M3 was co-integrated with GDP. The Granger causality test showed a bidirectional causality between M1 and GDP and a unidirectional causality from GDP to M2 and M3.

Ramdhan et al. (2018) investigated the co-integration relationships between the S&P 500 index and the GDP, inflation rate, broad money supply, and long term interest rate in the US. Also, the same relationships were investigated in Japan using the Nikkei 225 index. The study period was from 1990 until 2017 and data were quarterly. The authors used the Johansen (1988, 1991) co-integration tests and found that in both countries, there was co-integration between the US and Japan stock market indices and all macroeconomic variables. The US index and the Japanese index were positively related, in the long run, to each of the macroeconomic variables.

Malhotra (2018), using the Engle Granger residual based test of co-integration, reported that the BSE and Nifty Indian stock markets were co-integrated with the US NASDAQ and Dow Jones industrial average. This implied that these markets had long-term equilibrium relationships.

For the analysis, daily data were utilized for the period April 1, 2011 to October 31, 2017.

Kumar and Sahu (2017) reported on the co-integration between macroeconomic factors and the Islamic stock index on the Indian stock market. The macroeconomic factors considered were the whole sale price index, 365-day government of India T-bill rate, M3 money supply, exchange rate, and Dow Jones Islamic Market India Total Return Index. The study was on monthly data over the period January 2006 to July 2015. Johansen's multivariate co-integration test and the vector error correction model (VECM) were employed in the study. Results indicated that there were co-integration or long-term relationships between the Islamic stock index and whole sale price index, money supply, and interest rate (T-bill rate). The long-term relationships were positive for money supply and the whole sale price index and negative for the interest rate. The Granger causality test showed that money supply and exchange rate caused the Islamic India market index

Kisswani et al. (2015) examined the co-integration and causality between foreign direct investment (FDI) and GDP in Estonia. The quarterly data were over the period 1994-Q1 to 2013-Q2. Co-integration was determined by using the Engle and Granger residual-based test and the Johansen trace and eigenvalue tests. Also, the causal relationship was examined using the Granger test. Results of the Johansen tests showed that FDI and GDP were integrated with one integrating equation. The Granger causality test indicated that FDI caused GDP, but GDP did not cause FDI.

Camareroa et al. (2015) examined long-term or equilibrium relationships through co-integration between energy use and GDP for 15 EU countries. Applying a non-linear co-integration test (Chong, 2008), the authors reported co-integration between energy use and GDP for Spain, Austria, Denmark, Portugal and the Netherlands. These countries had the widest gap in meeting their targets of reduced emissions under the Kyoto Protocol.

Gopinathan et al. (2015) investigated the co-integration relation between the S&P 500 and the real GDP using quarterly data over the period 1970-Q1 to 2013-Q3. The authors examined the co-integration for the whole sample and for rolling samples of 100 observations over time. Results from the Johansen test indicated that the S&P 500 index was co-integrated with GDP for the whole period and for the window of 100 observations over time, except for the economic crisis period, 2008Q1 to 2008Q4, where no co-integration relationship existed between the two variables

Ivanov (2011) examined the influence of the crisis on financial markets by studying the co-integration relationship between the S&P 100 and S&P 500 indexes in extreme market conditions using the Johansen trace test. The author used one-minute interval data. Results showed that there was no co-integration between the two indexes for the day after Black Monday and the time of the Japanese earthquake.

DATA

Quarterly data over the years 1970-Q1 to 2018-Q1 were gathered on the following variables: S&P 500 (SP), Dow industrial average (Dow), GDP (billions), unemployment rate, savings deposits at commercial banks (billions), M2 money supply (billions), National debt (billions), inflation (CPI), crude oil import price in dollars per barrel, industrial production index, 10-year bond rate, trade balance(Millions), and federal fund rate. The data were retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org

METHODS

Dow, S&P, and GDP were tested for co-integration with each other and with each of the macroeconomic variables above. We report here on results from the Johansen co-integration test and the Vector Error Correction analysis concerning the variables that were co-integrated. Also, we report on the relationships between variables using the Granger test.

Co-integration and vector error correction model

Two non-stationary time series are co-integrated if there is a linear combination of the two variables that is stationary or I(0). Two co-integrated variables that are I(1) (i.e., stationary upon first difference) can be analyzed using the Vector Error Correction Model (Johansen, 1988, 1991). For two variables with one co-integrated vector, the model can be expressed as:

$$D\_Y_{it} = C + \alpha\beta' Y_{it-1} + \sum_{i=1}^{p-1} \delta i \, D\_Y_{it-1} + E \quad (1)$$

Where C is a constant, D_Y_{it} is a 2x1 column vector of first differences for the two variables (y_{1t}, y_{2t}), α is a 2x1 column vector, β' is a 1x2 row vector, δ_i is a 2x2 matrix, and E is the random error term. The expression $\alpha\beta' Y_{it-1}$ gives the long-term relationship or equilibrium between the two variables, and $\sum_{i=1}^{p-1} \delta i \, D\_Y_{it-1}$ gives the short-term relationship.

The value p, for the number of lags, can be chosen based on the Schwartz and Akaike criteria. The normalized co-integrated vector, $(1, -\beta_2)\ Y_{it} = y_{1t} - \beta_2\ y_{2t}$, gives the long-term linear relationship between the two variables. This implies that, at equilibrium, $y_{1t} = \beta_2\ y_{2t}$. The elements of the α column vector give the speed by which the change in the dependent variables returns to the equilibrium value when deviations from equilibrium occur. This is given by the following equations:

$$D\_y_{1t} = \alpha_1 (y_{1t-1} - \beta_2 y_{2t-1}) \tag{2}$$

$$D\_y_{2t} = \alpha_2 (y_{1t-1} - \beta_2 y_{2t-1}) \tag{3}$$

Multiplying both sides of (3) by β2 and subtracting the two equations, one arrives at the following relationship:

$$y_{1t} - \beta_2\ y_{2t} = (1 + \alpha_1 - \alpha_2\ \beta_2)\ (y_{1t-1} - \beta_2 y_{2t-1}) \tag{4}$$

The absolute value of $(1+\alpha'\beta)$ or Abs $(1 + \alpha_1 - \alpha_2\beta_2)$ must be less than 1 for the long run linear relationship, $(y_{1t} - \beta_2 y_{2t})$, to be stationary.

Granger Causality Test

The Granger causality test (Granger, 1969) is used to determine whether one time series can forecast or predict another. The idea of forecasting or prediction is more relevant than testing whether Y causes or Granger-causes X, as is commonly asserted in the literature. According to *Diebold (2007) and Leame (1985), t*he term "causality" is a misnomer

The Granger test for two stationary time series, y, and x, involves regressing y on its own lags and the lags of x. One accepts the null hypothesis that *x* does not predict *y* if no lagged values of *x* are significant in the linear regression. Likewise, one can regress x on its own lags and the lags of y. In this case, y does not predict x if no lagged values of y are significant in the regression.

RESULTS AND DISCUSSION

Results of the Johansen co-integration analysis are presented in Table 1. From the trace test, it is seen that each pair of variables is integrated with one co-integration factor (r=1). If one considers the series Dow and GDP, one finds that the null hypothesis that there is zero integration vector (r =0) is rejected since the observed trace statistic of 50.02 is larger than the 5% level critical value of 19.99. The null hypothesis that there is one co-integration vector (r=1) is accepted since the trace statistics of 3.52 is less than the critical value of 9.13.

The test result for Dow and GDP is the same for all the other pairs of time series, showing that the time series are co-integrated with only one co-integration vector, as expected.

Estimates of α_1, α_2, β_2 and the long-term linear relation (y_{1t} - β_2 y_{2t}) from the VECM (1) in equation (1) are presented in Table 2. The estimate β_2 is positive, according to expectation, since the two variables under consideration move together in a common trend ($y_{1t} = \beta_2 y_{2t}$). Also, it is seen that the Abs ($1 + \alpha_1 - \alpha_2\beta_2$) < 1, which indicates that the long-term linear relationship or equilibrium between the two series under consideration is stationary, as expected. The estimates α_1 and α_2 in Equations (2) and (3) are small in magnitude, which shows that the time series return slowly to their equilibrium value when deviations from equilibrium occur.

Table 3 presents the co-integration results for the same series in Table 2, but for the period after 2007-Q4. This period is characterized by stock market volatility. It is interesting to see that the same co-integrated relationships still hold for this period. The equilibrium relationships are also stationary as indicated by the fact that Abs ($1 + \alpha_1 - \alpha_2\beta_2$) < 1. It is interesting to note, however, that the estimates of α_1 and α_2 are larger than those in Table 2. This implies that the speed of return to equilibrium is faster for this period. Also, Abs ($1 + \alpha_1 - \alpha_2\beta_2$) is smaller than that of Table 2.

Table 4 presents the short-term Granger analysis for each pair of variables. Associated with each of the tests, are the short-term results from the VECM (1) in Equation (1). For the sake of space, we present only the significant short-term relationships between two variables from the vector error correction model involving one co-integration vector, VECM (1)

In what follows, it is seen that there is good agreement between the short-term Granger test results and the short-term VECM (1) results. Table 4 shows that Dow predicts or influences GDP, but GDP does not influence Dow. This is in agreement with the results in Table 5, showing that only Dow influences GDP. The effect was positive. The GDP effect on the Dow was not significant and, therefore, not presented.

There is a bilateral relationship between Dow and Savings (Table 4). This relationship is shown in Table 6, where Dow had a negative effect on Savings and Savings had a negative effect on Dow. Likewise, Dow predicts Debt, and Debt predicts Dow (Table 4). The VECM (1) results in Table 7 also show that Dow predicts Debt and Debt predicts Dow. The sign is negative for the first lags and positive for higher lags.

It is seen from Table 4 that SP predicts GDP, but GDP does not predict SP. This is similar to the results between GDP and Dow. Table 8 results from the VECM (1) analysis are in agreement by showing that SP has a positive effect on GDP, but GDP does not influence SP. The Granger test shows that Debt predicts SP, but SP does not predict Debt. The associated results from Table 9 also show that Debt predicts SP, but SP does not predict Debt. SP and Savings have bilateral relationships (Table 4). Results from the VECM (1) in Table 10 show that SP has a negative relationship with Savings, but Savings do not influence SP. Of interest, is the finding that SP predicts Dow (significance at the 10% level). However, Dow has no significant relationship with SP. Results from the VECM (1) analysis show that Dow and SP were not related. The Granger test shows that CPI predicts SP, but the reverse is not true. Results from Table 11 show that CPI has a negative relationship with SP. SP influences CPI but was not significant at the 5% level.

The relationships between GDP, Savings, and CPI from the Granger test are presented in Table 4 and the associated VECM (1) results in Tables 12 to 14. GDP and Debt have a bilateral relationship, as seen in Table 4. The VECM (1) results in Table 12 show that GDP predicts Debt and Debt predicts GDP. GDP has a negative effect on Debt and Debt has a negative effect for the first lag, The Granger test shows that GDP and Savings have dual relationships. Results from The VECM (1) analysis (Table 13) show that GDP has a negative effect on Savings and Savings a negative effect on GDP. The Granger test in Table 4 shows that CPI predicts GDP, but GDP does not predict CPI. Results from Table 14 confirm that CPI has a negative and significant effect on GDP, but GDP has no effect on CPI.

TABLE 1. CO-INTEGRATION RESULTS FOR PAIRS OF VARIABLES USING THE JOHANSEN TRACE TEST

Dow, GDP			
H_0	H_1	Trace	Critical Value
Rank = r	Rank > r		
0	0	50.02	19.99
1	1	3.52	9.13
Dow, savings			
H_0	H_1	Trace	Critical Value
Rank = r	Rank > r		
0	0	55.07	19.99
1	1	2.86	9.13
Dow, Debt			
H_0	H_1	Trace	Critical Value
Rank = r	Rank > r		
0	0	21.59	19.99
1	1	7.15	9.13
SP, GDP			
H_0	H_1	Trace	Critical Value
Rank = r	Rank > r		
0	0	27.69	19.99
1	1	4.02	9.13
SP, Debt			
H_0	H_1	Trace	Critical Value
Rank = r	Rank > r		
0	0	22.73	19.99
1	1	6.65	9.13
SP, Savings			
H_0	H_1	Trace	Critical Value
Rank = r	Rank > r		
0	0	26.36	19.99
1	1	3.36	9.13
SP, Dow			
H_0	H_1	Trace	Critical Value
Rank = r	Rank > r		
0	0	20.94	19.99
1	1	8.68	9.13

SP, CPI			
H_0	H_1	Trace	Critical Value
Rank = r	Rank > r		
0	0	34.40	19.99
1	1	5.05	9.13
GDP, Debt			
H_0	H_1	Trace	Critical Value
Rank = r	Rank > r		
0	0	39.77	19.99
1	1	3.74	9.13
GDP, Savings			
H_0	H_1	Trace	Critical Value
Rank = r	Rank > r		
0	0	46.00	19.99
1	1	6.36	9.13
GDP, CPI			
H_0	H_1	Trace	Critical Value
Rank = r	Rank > r		
0	0	46.83	19.99
1	1	8.23	9.13

TABLE 2. CO-INTEGRATED VARIABLES AND LONG-TERM EQUILIBRIUM RELATIONSHIPS FROM THE VECTOR ERROR CORRECTION MODEL. DATA USED WERE QUARTERLY OVER THE PERIOD 1970-Q1 TO 2018-Q1

Cointegrated variables	Linear combination of the two variables at equilibrium	Speed of adjustments ($\alpha 1$ and $\alpha 2$) to deviations from equilibrium	Abs $(1 + \alpha_1 - \alpha_2\beta_2) < 1$ for stationarity of the linear combination
Dow, GDP	Dow - 2.769 GDP	Dow: - 0.00837 = α_1 GDP: - 0.00196 = α_2	0.99705
Dow, Savings	Dow - 11.394 Savings	Dow: -0.01022 = α_1 Savings: -.0002988 = α_2	0.99318
Dow, Debt	Dow -3.02927 Debt	Dow: -0.01358 = α_1 Debt: -0.00282 = α_2	0.99496
SP, GDP	SP - 0.24487GDP	SP: - 0.01763 = α_1 GDP: - 0.02222 = α_2	0.98781
SP, Debt	SP - 0.28009 debt	SP: - 0.01458 = α_1 Debt: -0.04176 = α_2	0.99711
SP, Savings	SP – 0.58625Savings	Sp: -0.00574 = α_1 Savings: -0.00473 = α_2	0.99703
SP, Dow	Dow - 9.34154 SP	Dow: -0.06081= α_1 SP: 0.00267 = α_2	0.91425
SP, CPI	SP - 34.09574 CPI	SP: -0.01741 = α_1 CPI: 0.00002844 = α_2	0.98162
GDP, Debt	GDP - 0.38290 Debt	GDP: 0.00689 = α_1 Debt: 0.02755 = α_2	0.99634
GDP, Savings	GDP- 0.7449 Savings	GDP: 0.00120 = α_1 Savings: 0.00417 = α_2	0.99809
GDP, CPI	GDP - 332.92945 CPI	GDP: - 0.00274 = α_1 CPI: 0.00000441 = α_2	0.99579

TABLE 3. CO-INTEGRATED VARIABLES AND LONG-TERM EQUILIBRIUM RELATIONSHIPS FROM THE VECTOR ERROR CORRECTION MODEL. DATA USED WAS QUARTERLY OVER THE PERIOD 2008-Q1 TO 2018-Q1

Cointegration 2008-Q1 to 2018-Q1	Linear combination of the two variables at equilibrium	Speed of adjustments ($\alpha 1$ and $\alpha 2$) to deviations from equilibrium	Abs $(1 + \alpha_1 - \alpha_2\beta_2) < 1$ for stationarity of the linear combination
Dow, debt	Dow -1.41828 Debt	Dow: 0.06617 = α_1 Debt: 0.10592 = α_2	0.91594
Dow, GDP	Dow -2.54749 GDP	Dow: -0.38014 = α_1 GDP: -0.04038 = α_2	0.72272
Dow, Savings	Dow -2.21914 Savings	Dow: -0.08912 = α_1 Savings: -0.03328 = α_2	0.98473
SP, debt	SP - 0.26170 Debt	SP: - 0.13486 = α_1 Debt: 0.29947 = α_2	0.78677
SP, GDP	SP - 0.33218 GDP	SP: - 0.37957 = α_1 GDP: - 0.26819 = α_2	0.70952
SP, Savings	SP - 0.31962 Savings	SP: - 0.50364 = α_1 Savings: -0.07324 = α_2	0.51977
SP, Dow	SP - 0.12516 Dow	SP: - 0.36586 = α_1 Dow: -1.35342 = α_2	0.80353
SP, CPI	SP -132.48593 CPI	SP: - 0.12667 = α_1 CPI: 0.00020369 = α_2	0.84635
GDP, Debt	GDP --1.41828 Debt	GDP: 0.06617 = α_1 Debt: 0.10592 = α_2	0.91594
GDP, Savings	GDP -1.22919 Savings	GDP: - 0.20875 = α_1 Savings: -0.02276 = α_2	0.81922
GDP, CPI	GDP -479.28654 CPI	GDP: - 0.04059 = α_1 CPI: 0.00018366 = α_2	0.87141

TABLE 4. GRANGER TESTS FOR PAIRS OF VARIABLES

	Chi-square	P > Chi-square
Dow predicts GDP	15.45	0.0015
GDP predicts Dow	2.23	0.5264
Dow predicts savings	12.06	0.0169
Savings predicts Dow	8.58	0.0726
Dow predicts Debt	11.14	0.0486
Debt predicts Dow	25.36	0.0001
SP predicts GDP	16.31	0.0060
GDP predicts SP	3.65	0.6014
SP predicts Debt	8.71	0.1213
Debt predicts SP	29.00	0.0001
SP predicts savings	12.94	0.0116
Savings predicts SP	10.08	0.0391
SP predicts Dow	7.83	0.0978
Dow predicts SP	6.66	0.1552
SP predicts CPI	6.84	0.2327
CPI predicts SP	22.79	0.0004
GDP predicts Debt	25.67	0.0023
Debt predicts GDP	38.89	0.0001
GDP predicts savings	21.05	0.0003
Savings predicts GDP	27.28	0.0001
GDP predicts CPI	3.36	0.3391
CPI predicts GDP	8.37	0.0389

TABLE 5. THE SHORT-TERM SIGNIFICANT RELATIONSHIP, FROM THE VECM (1), BETWEEN DOW AND GDP. D REFERS TO THE FIRST DIFFERENCE

Dependent		Estimate	Std. Error	T Ratio	Prob>|T|
D_GDP(t):					
	Independent variables:				
	D_Dow(t-1)	0.03119	0.00930	3.35	0.0010
	D_GDP(t-1)	0.23023	0.07808	2.95	0.0036
	D_Dow(t-2)	0.02369	0.00963	2.46	0.0148

TABLE 6. THE SHORT-TERM SIGNIFICANT RELATIONSHIP, FROM THE VECM (1), BETWEEN DOW AND SAVINGS. D REFERS TO THE FIRST DIFFERENCE

Dependent		Estimate	Std. Error	T Ratio	Prob>|T|
D_Dow(t)	Independent:				
	D_Dow(t-1)	0.17072	0.07613	2.24	0.0262
	D_Sav(t-1)	-2.22536	1.32454	-1.68	0.0947
	D_Dow(t-3)	0.14063	0.07611	1.85	0.0663
D_Savings(t)					
	D_Dow(t-1)	-0.01471	0.00397	-3.70	0.0003
	D_Sav(t-1)	0.38474	0.06907	5.57	0.0001
	D_Sav(t-3)	0.41316	0.07376	5.60	0.0001

TABLE 7. THE SHORT-TERM SIGNIFICANT RELATIONSHIP, FROM THE VECM (1), BETWEEN DOW AND DEBT. D REFERS TO THE FIRST DIFFERENCE

Dependent		Estimate	Std. Error	T Ratio	Prob>|T|
D_Dow(t)	Independent				
	D_Dow(t-1)	0.14868	0.07937	1.87	0.0627
	D_Debt(t-1)	-0.67349	0.39239	-1.72	0.0878
	D_Debt(t-2)	1.26685	0.38845	3.26	0.0013
	D_Dow (t-3)	0.13161	0.08041	1.64	0.1035
D_Debt(t)					
	D_Dow(t-1)	-0.03731	0.01658	-2.25	0.0257
	D_Debt(t-1)	0.27279	0.08196	3.33	0.0011
	D_Debt(t-2)	-0.15220	0.08114	-1.88	0.0623
	D_Debt(t-3)	0.22418	0.08440	2.66	0.0086
	D_Dow(t-4)	0.03276	0.01692	1.94	0.0544
	D_Debt(t-4)	0.29264	0.08477	3.45	0.0007

TABLE 8. THE SHORT-TERM SIGNIFICANT RELATIONSHIP, FROM THE VECM (1), BETWEEN SP AND GDP. D REFERS TO THE FIRST DIFFERENCE

Dependent		Estimate	Std. Error	T Ratio	Prob>|T|
D_GDP(t)	Independent				
	D_GDP(t-1)	0.24260	0.08022	3.02	0.0029
	D_SP(t-1)	0.21318	0.08289	2.57	0.0109
	D_SP(t-2)	0.21946	0.08425	2.60	0.0099
D_SP(t)					
	D_SP(t-1)	0.14739	0.08456	1.74	0.0830

TABLE 9. THE SHORT-TERM SIGNIFICANT RELATIONSHIP, FROM THE VECM (1), BETWEEN SP AND DEBT. D REFERS TO THE FIRST DIFFERENCE

Dependent		Estimate	Std. Error	T Ratio	Prob>|T|
D_Debt(t)	Independent				
	D_Debt(t-1)	0.30005	0.08118	3.70	0.0003
	D_Deb(t-2)	-0.15910	0.08229	-1.93	0.0547
D_SP(t)					
	D_Debt(t-1)	-0.00012716	0.00004137	-3.07	0.0024
	D_Debt(t-2)	0.00012787	0.00004193	3.05	0.0026
	D_SP(t-2)	0.13108	0.07559	1.73	0.0846

TABLE 10. THE SHORT-TERM SIGNIFICANT RELATIONSHIP, FROM THE VECM (1), BETWEEN SP AND SAVINGS. D REFERS TO THE FIRST DIFFERENCE

Dependent	Independent	Estimate	Std Error	T Ratio	Prob>|T|
D_SP(t)					
	D_SP(t-1)	0.15980	0.07314	2.18	0.0302
	D_SP(t-3)	0.19168	0.07278	2.63	0.0092
D_Savings(t)					
	D_SP(t-1)	-0.11322	0.03394	-3.34	0.0010
	D_Sav(t-1)	0.41592	0.06845	6.08	0.0001
	D_Sav(t-3)	0.41606	0.07218	5.76	0.0001

TABLE 11. THE SHORT-TERM SIGNIFICANT RELATIONSHIP, FROM THE VECM (1), BETWEEN SP AND CPI. D REFERS TO THE FIRST DIFFERENCE

Dependent	Independent	Estimate	Std. Error	T Ratio	Prob>|T|
D_SP(t)					
	D_SP(t-1)	0.13634	0.07652	1.78	0.0765
	D_CPI(t-2)	-25.72336	11.83715	-2.17	0.0311
	D_SP(t-3)	0.26281	0.07464	3.52	0.0005
	D_CPI(t-3)	-28.84649	11.93745	-2.42	0.0167
D_CPI(t)					
	D_CPI(t-1)	0.34898	0.07478	4.67	0.0001
	D_SP(t-3)	0.00087916	0.00049544	1.77	0.0777

TABLE 12. THE SHORT-TERM SIGNIFICANT RELATIONSHIP, FROM THE VECM (1), BETWEEN GDP AND DEBT. D REFERS TO THE FIRST DIFFERENCE

Dependent		Estimate	Std. Error	T Ratio	Prob>|T|
D_GDP(t)	Independent				
	D_GDP(t-1)	0.28579	0.07880	3.63	0.0004
	D_Deb(t-1)	-0.19035	0.05211	-3.65	0.0003
	D_GDP(t-2)	0.21177	0.08165	2.59	0.0103
	D_Deb(t-2)	0.10744	0.05132	2.09	0.0378
D_Debt(t)					
	D_Deb(t-1)	0.14413	0.08440	1.71	0.0896
	D_GDP(t-2)	-0.43853	0.13225	-3.32	0.0011
	D_Deb(t-2)	-0.16349	0.08313	-1.97	0.0509
	D_GDP(t-3)	-0.28188	0.13837	-2.04	0.0432

TABLE 13. THE SHORT-TERM SIGNIFICANT RELATIONSHIP, FROM THE VECM (1), BETWEEN GDP AND SAVINGS. D REFERS TO THE FIRST DIFFERENCE

Dependent		Estimate	Std. Error	T Ratio	Prob>|T|
D_GDP(t)	Independent				
	D_GDP(t-1)	0.35229	0.07136	4.94	0.0001
	D_Sav(t-1)	-0.34288	0.15617	-2.20	0.0294
	D_Sav(t-3)	0.40930	0.15406	2.66	0.0086
D_Savings(t)					
	D_GDP(t-1)	-0.15033	0.03054	-4.92	0.0001
	D_Sav(t-1)	0.33380	0.06685	4.99	0.0001
	D_Sav(t-3)	0.40638	0.06594	6.16	0.0001

TABLE 14. THE SHORT-TERM SIGNIFICANT RELATIONSHIP, FROM THE VECM (1), BETWEEN GDP AND CPI. D REFERS TO THE FIRST DIFFERENCE

Dependent		Estimate	Std. Error	T Ratio	Prob>|T|
D_GDP(t)	Independent				
	D_GDP(t-1)	0.40266	0.08009	5.03	0.0001
	D_GDP(t-2)	0.26628	0.08078	3.30	0.0012
	D_CPI(t-2)	-25.55167	12.09604	-2.11	0.0361
D_CPI(t)					
	D_CPI(t-1)	0.30063	0.08207	3.66	0.0003

CONCLUSION

In this study, we investigated co-integration and long-term relationships between macroeconomic time series using the Johansen test and the Johansen Vector Error Correction Model (VECM). Also, short-term relationships between time series were determined from the Granger test and the VECM (1). Results showed that the Dow index was co-integrated with GDP, debt, S&P 500 index, and savings deposits. The S&P 500 index was co-integrated with Dow, GDP, debt, savings deposits, and CPI. GDP was co-integrated with CPI, savings deposits, debt, S&P 500, and Dow.

Inflation, debt, and savings deposits were the macroeconomic variables co-integrated with Dow, S&P 500, and GDP. The long-term linear relationships at equilibrium between the variables were of the form ($Y_{1t} - \beta_2 Y_{2t}$). The error correction rates for deviations from the long-term equilibrium were small in magnitude, less than 4% per quarter. This was for the period from 1970-Q1 to 2018-Q1.

For the period from 2008Q1 to 2018Q1, where the stock market showed considerable volatility, the error correction rates were considerably higher, with the highest being 50%.

Using the Granger test and the VECM (1), the short-term relationship showed that Dow and debt had a bilateral relationship. Dow and savings deposits also had a bilateral relationship.

Dow had a positive effect on GDP, but GDP did not affect Dow.

SP had a bilateral relationship with savings deposits. SP had an effect on GDP. Debt and CPI had an effect on SP. There was no significant relationship at the 5% level between SP and Dow.

GDP had a bilateral relationship with debt and with savings deposits. Inflation had a negative effect on GDP, but GDP did not affect inflation.

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ENHANCING DATA MANAGEMENT EDUCATION THROUGH EXPERIENTIAL LEARNING

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ABSTRACT

The design and implementation of information systems contribute to the practical knowledge of students. This article introduces an active learning environment in an International Data Management course. Specifically, we highlight how classroom lectures can be enhanced by the experience and application of a real-world project-based study. Gold Rush Antiques is a real-world database management case. Gold Rush is a business with multiple locations which has experienced tremendous growth. The scenario engages students in the design and development of a database to advance the organization and analysis of the data. This case is created at various levels of data management coursework – beginning, intermediate, or advanced. The case scenario is written at a beginner level; teaching notes have intermediate and advanced suggestions (provided upon request). Students are requested to develop a working prototype of a database management system that includes the design of data, tables, forms, queries, and reports. The Gold Rush Antiques case study allows students to not only learn the development of a database but also understand how to examine, analyze, and apply business procedures.

Keywords: Database Case Project, Database Development, Management Information Systems, Database Management System, SQL

INTRODUCTION

In an increasingly data-centric business landscape, the ability to understand and manage data systems is no longer confined to the realm of information systems (IS) professionals. Business leaders are expected to make informed decisions based on structured, reliable data, which necessitates a foundational understanding of how data is stored, accessed, and analyzed (Laudon & Laudon, 2020). Despite this reality, many undergraduate business programs continue to underemphasize the technical competencies necessary to work effectively with data, particularly in database design.

In the context of database education, Coronel, Morris and Rob (2019) advocate for experiential exercises to reinforce database theory, whereas Rob and Coronel (2019) highlight the pedagogical benefits of simulating real-world scenarios. Research consistently supports the value of active learning in technical education. The teaching strategy draws on the principles of experiential learning (Kolb, 1984), situated learning (Lave & Wenger, 1991), and case-based reasoning (Aamodt & Plaza, 1994), offering a structured framework for building practical skills in tandem with conceptual knowledge. Freeman et al. (2014) demonstrated that active learning increases student performance in STEM disciplines, while Biggs and Tang (2011) emphasize the alignment of constructive alignment in course design, encouraging students to "learn by doing."

In Data Management courses, project-based learning (PBL) and real-world case studies enable students to apply data modeling, normalization, and querying techniques in authentic contexts (Kolb, 1984). Teaching database design within the business curriculum offers students critical skills that support data-driven decision-making, operational efficiency, and cross-functional communication. By integrating practical examples and real-world case studies, educators can enhance student engagement while demonstrating the tangible impact of well-structured data systems on business outcomes (Coronel et. al., 2019).

This paper argues that incorporating database design, supported by practical examples, is essential to preparing business students for modern, data-informed roles. To illustrate this, a detailed practical example of a retail data management system is included, demonstrating how database principles directly contribute to business performance. Through experiential learning, students not only develop technical competencies but also gain insights into how data underpins strategic thinking and facilitates competitive advantages in today's global market (McKinney & Kroenke, 2018; Nguyen et al., 2021). Case-based learning further reinforces knowledge by placing students in realistic roles that require decision-making and problem-solving (Herreid, 2011). Through such activities, students develop both cognitive and technical skills, including data design, systems thinking, and user experience considerations (Silberschatz et al., 2020).

The case example is a term-long database project for students enrolled in an introductory database management or information systems course. With the addition of increased complexity, the project may also be prepared for students in intermediate/advanced levels of database management, in addition undergraduate or graduate. To complete the project, the student will be exposed to various database development skills. Students will learn to: (1) understand the fundamentals of logical and physical data modeling by developing entity-relationship (ER) diagrams, including normalization; (2) create and populate database tables while applying business rules; and (3) create forms, queries, and reports. This project is designed for any relational database management system (DBMS), such as Microsoft Access, Oracle, Microsoft's SQL Server, or MySQL.

LITERATURE REVIEW

Active and Experiential Learning

Active learning methods such as PBL and case-based instruction have become prominent in engineering and computing education for their effectiveness in fostering deep learning (Michael, 2006; Bonwell & Eison, 1991). Kolb's experiential learning cycle (1984) identifies concrete experience, reflective observation, abstract conceptualization, and active experimentation as essential components, all of which are fulfilled in well-designed real-world projects.

Numerous studies have affirmed that incorporating real-life problems into coursework helps bridge the gap between academic theory and workplace application (Bransford, Brown, & Cocking, 2000; Savery, 2006). In particular, case-based learning supports the development of both procedural and declarative knowledge, encouraging students to engage in inquiry, dialogue, and synthesis (Herreid, 2001; Kim et al., 2006).

Information Systems Pedagogy

Within the field of information systems, hands-on database projects help students internalize key concepts such as normalization, data integrity, and ER modeling (Elmasri & Navathe, 2016; Silberschatz et al., 2020). According to Connolly and Begg (2015), students who work on applied system development tasks show higher mastery of relational design and query optimization. Additionally, peer collaboration in such environments supports social constructivist theories of learning (Vygotsky, 1978).

Recent studies also emphasize the importance of industry alignment in computing education, noting that students with experience in authentic projects are better prepared for real-world challenges (Denning, 2017; ACM/IEEE-CS, 2013). Projects that require user interface development and stakeholder analysis further simulate actual job requirements (Whitten et al., 2004).

CASE EXAMPLE

Gold Rush Antiques is a real-world database management case. Gold Rush is a business with multiple locations across north Georgia which has experienced growth. The scenario engages students in the design and development of a database to advance the organization and analysis of the data. This case is created at various levels of data management coursework – beginning, intermediate, or advanced. The case scenario is written at a beginner level; teaching notes have intermediate and advanced suggestions (provided upon request). Students are requested to develop a working prototype of a database management system that includes the design of data, tables, forms, queries, and reports. The Gold Rush Antiques case study allows students to not only learn the development of a database but also understand how to examine, analyze, and apply business procedures.

This teaching case is a semester-long team project designed to model an organization's data needs and will design and prototype a database application. The deliverables for the project should be due in several stages at various points throughout the semester. Each team's success will depend on being able to apply many of the course objectives (including data modeling, logical database design, etc.). In this team project, each team will model an organization's data needs and will design a prototype of a database application. Expectations for quality of design, professionalism, appropriate use of entity-relational diagramming techniques and complexity are rigorous. The project will involve the conceptual, logical and physical development of a database system, with a final day for discussion and walk through of each team's efforts. The details of the case requirements and project deliverables are explained in the next sections.

Case Opener

Gold Rush Antiques (aka Gold Rush) is a small and midsize business (SMB) that focuses on antiques and interior shop design located in Buford, Georgia. Gold Rush is a family-owned business of almost 20 years with multiple locations across the north Georgia region. Gold Rush has undergone incredible growth in the last few years with the opening of three (3) more shops in north Georgia (Dahlonega, Alpharetta, and Marietta).

Within each antique shop exists several booths. These booths house various vendors' goods separated based on vendor, product type, and other characteristics. Gold Rush refers to their vendors as "dealers" and within the shop, several different dealers provide goods and services for the customers who visit. The dealers display their products (i.e., antiques) for sale in individual booths within each Gold Rush shop. Dealers rent booth spaces, varying in size from small to large. Gold Rush earns revenue by taking a percentage of each dealer's sales, this covers Gold Rush's payroll for employees and other overhead expenses.

As a small family-owned business, Gold Rush could reach new heights. With the right system in place, Gold Rush has the capability of managing multiple shop locations and increasing sales. To address the tremendous growth and increase in presence, Gold Rush management faces two main challenges: they need to (1) have a centralized system to track the employee and dealer information for multiple shop locations and (2) prepare a sales management system (SMS) to manage sales transactions, booth-information, booth-locations, and product inventory. The growth of the business has been faster than Gold Rush management anticipated and the organization's obsolete method of using hand-written price tags, simple cash register transactions, and Excel spreadsheets is not sufficient to address their business needs (i.e., maintaining dealer and booth information, product data, employee payroll, and sales transactions).

The owner of Gold Rush recognizes the importance of using technology to maintain information and desires a centralized system across all locations to maintain efficiency and effectiveness. Thus, Gold Rush has chosen to utilize a database management system to maintain data about its employees, dealers, and customers. After interviewing several dealers and employees, the owner of Gold Rush prepared a database requirements report. This report includes business procedures, and the data required in the new system.

Business Procedures & Database Requirements

Gold Rush requires a centralized database that tracks dealers, booth-information at each location, dealer products at each location, to monitor current product inventory levels (quantity on hand, product costs, and selling prices) and sale transactions (by dealer and employee). Forms should be simple and effective to allow users to enter data about the dealers, booths (location, size, etc.), customer information, and dealer products. Reports explore dealer popularity, product information, and revenue. In addition, specific information about employees from the database for payroll purposes needs to be extracted – this may be outside of the current scope but a definite must for future system development.

Current Procedures

Employee

There are four types of employees at each location: cashier, sales associate, loader, and greeter (See Table 1). Employee information maintained includes their name, address, phone, email, employee type, and store. Employee payrate is based on experience and may be increased after a thirty (30) day probation period based on number of hours and performance. Gold Rush's current employee payroll process is based on the honor system. The employees hand writes the hours they work and give the manager each week. Often, they wait until the last day of payroll to document their hours, and this does not always result in an accurate payroll. Additionally, the hours are not confirmed but based on trusting that the employee did in fact work on the days and times stated by them. Gold Rush employs all sales associates; dealers do not hire shop staff and may not have representatives actively selling in booths.

TABLE 1. GOLD RUSH ANTIQUES – SAMPLE EMPLOYEE JOB TITLES INFORMATION

Job Titles	Description
Greeter	Welcome customers to store; verify purchases; stand for a minimum of 4 hours
Inventory Handler	Organizes the inventory in the booths, stocks the inventory
Loader	Some retail experience required; Be able to lift and move furniture
Sales Associate	Some retail experience required with preferred merchandising experience; Effective communication skills necessary

Dealers & Booths

Dealer information is currently stored in excel spreadsheets. The spreadsheet has the dealer's name, address, phone number, and email (See Table 2). Other dealer information is gathered through an application process (e.g., website, social media tags, etc.). The booth type that the dealer has is stored with the dealer information. There are three types of booths: 8 x 10, 10 x 12, and 12 x 14. Each shop location has the same amount of each booth type. The shop layout is the same for each location. Booth rental prices are based on the shop, the exact booth location in each shop, and the size of booth. There are four shop-locales: Alpharetta, Buford, Dahlonega, and Marietta. A dealer may have only one booth at a single locale but may have a booth at multiple shop locales.

TABLE 2. GOLD RUSH ANTIQUES – SAMPLE DEALER INFORMATION EXCEL SPREADSHEET

Name	Address	Email	Phone
Matt Johnson	23 Park Place, Columbus, GA 31909	no3vintage@email.com	(678) 257-1313
Christina Berry	68 Oriental Avenue, Montgomery, AL 36106	brookstone@email.com	(706) 257-5679
James Brown	92 Charles Place, Birmingham, AL 35242	eaglesnest@email.com	(205) 257-3581
Johanna Walker	34 St James Place, Columbus, GA 31909	mypurpose@email.com	(706) 257-6190
Shelley Jones	59 Atlantic Way, Montgomery, AL 36106	greenacres@email.com	(334) 257-5574

A dealer must sign an initial six-month lease which then moves to a month-to-month lease afterwards with a month's deposit. The deposit represents the last month's rent once the dealer has provided a written notice of vacating the premises within the required thirty (30) days. Rent is due at the beginning of each month and may not be deducted from product sales. Gold Rush receives an 8% commission on each sales transaction. There is also a service charge of 4% for all credit card transactions. Each dealer gets a sales payout at the end of each month.

Products

Each dealer may fill their booth with any type of products. However, sixty percent (60%) of products must be considered as antique or vintage and the other forty percent (40%) may be a mix of product types (See Table 3). Each dealer will need to describe their products and explain how they meet these standards in the dealer application form. Additional characteristics of products are also collected (name, price, color, material, type, where type is furniture, pottery, jewelry, etc.). This is a stand-alone form created once the dealer has been approved. This allows the dealer to fill in this form every time updates are made to their inventory. The dealer is responsible for getting the products to the shop and into the booth, but the Gold Rush inventory handler verifies and stocks the products to give a consistent look across the Gold Rush shops. It is the dealer's responsibility to market their booth and products.

TABLE 3. GOLD RUSH ANTIQUES – SAMPLE PRODUCT CATEGORIES INFORMATION

Product Categories
Memorabilia
Vintage Vinyl
Coca Cola
Furniture
Military Antiques
Photography & Paintings
Toys
Pottery
Holiday Items
Jewelry

Dealers may sell as many products as they can fit in the given booth space. Although dealers may sell similar product types, their products are assigned individual product numbers. This is how Gold Rush identifies whose products are purchased. This also allows the creation of reports at the end of the month, generated by Gold Rush, to determine the number of sales per dealer and the Gold Rush commission.

Sales

Currently, each dealer must create their own sales label. These labels contain a description of the product and the price that the dealer is selling it for. When working with many different dealers, it becomes difficult to check customers out because the dealers' labels are difficult to decipher. This upsets the customers at the cash register as the transactions take a long time because the employees cannot clearly read the labels. Sample Customer data is provided in Table 4.

Going forward, Gold Rush would like to implement some standards with respect to its sales process. Creating standard print labels makes it easier to identify the product information and its associated dealer. They do not wish to burden their own staff with attempting to label and manage the information, so a form in which the Dealers can fill out and provide all the pre-identified information is needed. This form and data are collected initially with the application and then each time the dealer wishes to stock more inventory in their booth (weekly or monthly). This will require a system that pre-assigns product numbers and requests any other pre-identified attributes (e.g., standard product type or characteristic list/dropdown). By digitizing and automating these processes, the employees should be able to easily search, scan or enter information upon the sales transaction. After the information is entered, several documents are created: (1) a receipt for the customer, (2) a copy of the receipt for Gold Rush documentation, and (3) a list of products that are picked up at the loading dock for the loaders to prepare.

TABLE 4. GOLD RUSH ANTIQUES – SAMPLE CUSTOMER INFORMATION

Name	Address	City, State, and Zip	Phone
Alenjandro Roller	916 Ridgecrest	Canton, GA 30115	(999) 844-4021
Allan Morgan	1022 Madison Way	Dahlonega, GA 30597	(999) 751-4445
Keisha Moderna	1209 North Avenue	Cartersville, GA 30120	(444) 330-1838
Terry Jones	6721 Bunker Hill Way	Ellijay, GA 30540	(444) 348-1085
Katherine Simmons	46451 Nash Lane	Ellijay, GA 30540	(773) 536-8481
Donny Walker	1190 Meridian	Buford, GA 30519	(312) 337-3822
Ebony Strong	1600 Minnesota Street	Dallas, GA 30157	(272) 285-1386
Henry Westland	3844 Stone Mountain	Dallas, GA 30157	(272) 331-0574
Joseph Keck	4116 Pinnacle Square	Blue Ridge, GA 30513	(555) 715-1988
Jacob Beath	6502 Oak Ridge Ct	Marietta, GA 30067	(312) 335-6232
Lionel Mason	2335 Hiatus Road	Marietta, GA 30067	(888) 212-7958
Leigh Ellen March	5606 Pines Blvd	Blairsville, GA 30721	(999) 307-3629
Montgomery Grant	12013 Hollywood Drive	Alpharetta, GA 30009	(312) 281-3418

Forms Requirements

Administrators and employees at Gold Rush would like to have user-friendly forms to ease the process of entering data related to dealers, customers, products, etc. Input forms, data entry forms, and application forms, complex forms including data from multiple tables, are requested to accomplish their goals.

Input/Query Forms

Various stakeholders desire the ability to enter, edit, or query data. Input forms must include labels consisting of descriptive names that represent the business.

Create Input/Query forms for the following tables:

Remember attributes are developed from the functional requirements mentioned throughout this case

- Employee information
- Dealer information
- Booth information
- Shop information
- Product
- Customer
- Sale information
- Any other associated tables

Application Forms

The information arrives from various stakeholders and application forms may be designed to add new information related to the combined data. These forms may include split forms, simple forms, multiple item forms, and/or navigation forms.

1. **Dealer Entry Form:** This should include the dealer's information and the requested application information.
2. **Product Entry Form:** List the project name and characteristics labeled in the functional requirements. Don't forget to assign a unique identifier for each product within each product category.
3. **Transaction Forms:** This is your sales transaction. As the cashier is checking the customer out, they need to collect information related to the sales transaction. Display the employee ID, date, time, sales transaction number, product purchases for that transaction along with the dealer for each product, and any other additional information related to the sales transaction.

Queries Requirements

A variety of queries are required to extract meaningful and accurate data. For Gold Rush management and staff to be more efficient and effective with their customers, packaging and logistics, data must be extracted and filtered to answer fundamental and essential questions. We have determined that the initial queries to be included in the database are below.

All query column headings are to be clear, concise, and accurately describe the contents of the column to the average user. Only universally accepted abbreviations are to be used. The queries are to be named as they are listed below.

1. **Dealer List:** List Dealer First and Last Name, Address (all parts), phone, email, webpage, and social media tag.
2. **Dealer-Booth List by Shop:** List each Shop with their corresponding booth types and dealers who currently rent.
3. **Booth Availability:** List all booths by shop that are currently available (not rented). Be certain to include their size and fee.
4. **Product List by Booth:** List booth ID, product ID, product name, product type, quantity on hand, and price. Format price as currency. The result should be sorted in ascending order by name.
5. **Customer Product Statistics:** Display customer name, product price, revenue, and total amount of each transaction (including tax). Format the necessary columns as currency.
6. **Product Margin:** Display by month the Location, Product Price, Product Cost, Total Product Margin (cost/price). Note: Product Margins are generally displayed in percentages.
7. **Dealer Monthly Sales:** Display the month, location, dealer information, total sales, and monthly commission.
8. **Shop Sales:** Display total sales by shop. Show shops, city, and total sales. Sort by shop.

Reports

Gold Rush requires several reports for the management team to analyze. The report requirements appear below. Label all sub-totals and grand totals appropriately with user-friendly descriptions to the left of the totals. Finally, to provide a more detailed and accurate appearance, all sub-totals should have a line above the subtotal and the grand total should have a double line above the total.

1. **Dealer Reports:**
   a) **Product Sales by Category:** This report provides a list of sales transactions based on categories over weeks/months by Dealer. Display the Dealer and their product sales by category. Total columns represented are Total Sales by Product, Total Product Per Category, and Total Sales by Product Category.
   b) **Dealer Monthly (or Annual) Fees** This report highlights for the Dealer the costs/fees they are incurring each month (or year). Representing their monthly payments to Gold Rush and the percentage that Gold Rush charges for the sales conducted. Display the Dealer Name, Address Information, Email, and monthly charges for renting booth(s) and percentage taken from each sales transaction grouped by month. Total columns for month (and/or year).
2. **Booth Rental Status Report:** This report highlights the various booth rentals among the dealers at each store. Gold Rush would like to understand who rents a booth at which stores during each month. Display at minimum the Dealer Name, booths rented, fees collected for each booth, and among which stores. Group by Booth Size and then Store.
3. **Daily Detailed Revenue Report:** This report is based on the Daily Revenue. Display the Transaction Date, Location, Total Product Cost, Total Product Revenue (quantity * price), and Total Revenue (Product Revenue – Product Costs). Group by Transaction Date and Location. Provide totals of the Revenue by Location and the full report.
4. **Gold Rush Receipt:** The form allows the employee or customer to review their transaction purchase prior to finally submitting payment. This form is like a receipt and is to be formatted in columnar format. The display of transaction and payment information should include the following fields: Purchase Date, Transaction ID, Product Number, Product Name, Quantity, Price, Amount, Subtotal, Sales Tax, and Total Amount Due. The Subtotal, Sales Tax Amount, and Total Amount Due should be calculated fields based on amount and shipping fee totals. Recall, the sales tax rate is 8%.

DELIVERABLES

Milestone One

Milestone One includes the following:

1. Write an executive summary. This should be a 1–2 pages project overview. It should briefly describe the initial analysis of the business scenario provided as it pertains to designing a

database application. It should communicate clearly what it is you think the system you intend to develop will do in terms of specific functionality that your final product will offer. The executive summary should be as detailed as possible. Some assumptions may be made (in the early phases it is often the case that some things are a little fuzzy), but these must be reasonable and defensible within the context of the Gold Rush scenario. The customer is not a technical person so there should be little to no technical jargon that may confuse them.
2. Create an entity-relationship diagram (ERD). Provide a conceptual data model for your proposed system using a suitable graphical modeling representation. Use any tool you choose to create the ERD. Normalization is a necessary process to ensure that all tables and fields meet integrity requirements, reduce redundancy, and ensure a well-structured database. Final ERD diagrams should be in third-normal form with no transitive or functional dependencies. All attributes of the entities must be shown using appropriate notation. Attributes that serve as identifiers must be underlined. Be sure to list all business rules and other assumptions.
3. Create a database structure. Show all relevant entities and their relationships, including the cardinalities of the relationships and participation requirements set by the Gold Rush Antiques scenario. Appropriate field names, data types, and field sizes should be used for all tables as described in the scenario.
4. Populate all tables with the sample data contained in the Gold Rush Antiques scenario (see Appendix) and any additional data provided by your instructor.

Milestone Two

Milestone Two includes the following:

1. Make corrections based on instructor feedback from Milestone One.
2. Review case study instructions for forms, queries, and reports. Create all needed forms, queries, and reports.
3. Create a simple logo for Gold Rush Antiques and incorporate in your forms and reports.
4. Navigational menu using the Switchboard Manager (advanced option).

Milestone Three

Milestone Three includes the following:

Develop your final prototype and written report.

1. Submit the completed prototype that illustrates your implementation of the work you have completed in prior milestones.
2. Demonstrate your command of tables, forms, queries, and reports, using whatever features are available in your given DBMS tool to make your prototype professional-looking and

functional. You can be as creative and ambitious as you wish. However, temper your creativity with the realization that a modest application that works well is better than a flashy one that crashes.
3. Submit documentation representing the creation of your prototype (e.g., database, SQL code, screenshots of forms, queries, reports, navigation menu, etc.).
4. Create a formal, professional group presentation demonstrating your prototype. It should be well organized and rehearsed. You must be prepared to address the overall scope and functionality of your project.

Case Conclusion

Gold Rush requires assistance. As the business has expanded, the demands and workload have increased. Gold Rush's decision to modernize its sales and inventory processes with a database will improve organization and profitability. Management is relying on your expertise to apply data management skills to address their business needs.

CONCLUSION

In contemporary education, passive lecture formats are increasingly insufficient to prepare students for the complexities of real-world data environments. Instead, educators are turning toward active learning frameworks that integrate practical application into theoretical instruction (Prince, 2004). The use of a real-world case study transforms the learning environment from passive reception to active construction of knowledge. As Dewey (1938) argued, education must be grounded in experience to be meaningful. The case study above allows students to *learn by doing* and practice problem-solving skills in a real-world context (Connolly & Begg, 2006). Gold Rush addresses the gap highlighted by Slonka and Bhatnagar (2024) that the design of relational databases is a difficult concept for students, especially with no previous or limited experience in design modeling. We strive to provide skillsets that (1) reinforce theoretical concepts learned in a database management course, (2) learn and perform critical thinking in determining end-user requirements and information necessary for data flow and entity relationship diagrams, and (3) practical experience in database development, including forms, queries, and reports. Hence, we highlight how classroom lectures are enhanced by the experience and application of a real-world project-based case study (Børte et al., 2023).

In conclusion, teaching database design to business students is not merely beneficial—it is crucial in the context of modern business operations. As companies increasingly rely on data for decision-making, the ability of business professionals to understand and work with data structures becomes indispensable (Kustitskaya et al., 2023). This case study has illustrated that incorporating database education into business curricula fosters analytical thinking, supports interdisciplinary collaboration, and enhances employability (Loyens et al., 2023). Ultimately, embedding database design principles into business education bridges the gap between theory and application, empowering students to leverage data as a strategic asset in their future careers (Rob & Coronel, 2019; Valacich & Schneider, 2017). As the demand for data-savvy business professionals continues to grow, academic institutions must adapt by prioritizing database competencies within business programs.

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STUDENT PERCEPTIONS OF AI IN UNIVERSITY STUDIES

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ABSTRACT

The integration of artificial intelligence (AI) in higher education is transforming students' learning experiences, decision-making, and academic efficiency. This study explores student perceptions of AI's benefits, challenges, and its role across academic disciplines. Findings indicate that while students recognize AI as a valuable educational tool, they also express concerns regarding privacy, reliance, and the need for improved AI training. Statistically significant differences were observed in AI's impact on learning efficiency, decision-making, and academic engagement, supporting the hypothesis that AI enhances education but presents notable challenges. The study also highlights the necessity for balanced AI integration, ensuring that AI complements rather than replaces critical thinking and independent learning. These insights provide valuable implications for educators and institutions in developing AI policies that optimize learning outcomes while addressing numerous concerns.

INTRODUCTION

Artificial intelligence (AI) has rapidly emerged as a transformative force in higher education, reshaping traditional learning methods and academic environments. As universities increasingly integrate AI into various aspects of instruction and administration, students are experiencing both the benefits and challenges of these technologies. AI applications such as personalized learning platforms, automated grading systems, and virtual tutors have demonstrated their potential to enhance learning efficiency, engagement, and decision-making processes.

However, the widespread adoption of AI in education also raises concerns about data privacy, over-reliance, and the need for adequate training to ensure effective utilization. While some students readily embrace AI as an essential learning tool, others remain skeptical about its impact on critical thinking and independent learning. Given these divergent perspectives, it is essential to examine how students perceive AI's role in their education, the challenges they encounter, and the extent to which AI supports or hinders their academic progress.

This study aims to explore student attitudes toward AI integration in university education, addressing key research questions related to AI's perceived benefits, limitations, and ethical implications. By analyzing student experiences across different disciplines, this research seeks to provide insights into how AI can be leveraged to improve learning outcomes while mitigating potential drawbacks. The findings will help inform educators and policymakers on best practices for AI integration in higher education, ensuring that AI technologies are implemented in a way that enhances rather than diminishes the educational experience.

LITERATURE REVIEW

The use of artificial intelligence (AI) in higher education has seen rapid growth, with AI being integrated into various aspects of university studies, including personalized learning, academic support, and administrative processes. Research indicates that AI technologies are becoming a fundamental part of university education, providing both opportunities and challenges for students and institutions alike (Holmes et al., 2023).

A systematic review by Holmes et al. (2023) analyzed 138 articles published between 2016 and 2022, highlighting the growing adoption of AI in educational settings. The study found that AI applications in higher education range from personalized learning platforms to automated grading systems and administrative support, significantly enhancing student engagement and institutional efficiency. Additionally, AI-driven tools such as chatbots and virtual tutors have been increasingly used to support students in their studies.

Studies have explored student perspectives on AI integration in academia. Kilianova et al. (2025) conducted a survey involving 378 university students and found that many students regularly use AI-based tools in their studies, expressing positive attitudes towards AI's role in facilitating learning. The study emphasized AI's transformative potential in improving educational outcomes, particularly in fields that require adaptive learning techniques. Similarly, Lee and Davis (2024) investigated the impact of generative AI in university-level English courses, demonstrating that AI-enhanced instruction improved student motivation, confidence, and interest in learning English as a foreign language.

Despite its advantages, AI integration in university studies presents several challenges. One major concern is data privacy, as AI tools often collect and analyze large amounts of personal information. Students may be wary of how their data is used and whether adequate protections are in place (Beshr et al., 2024). Another issue is algorithmic bias, where AI systems trained on biased data can perpetuate inequalities and lead to unfair academic outcomes (Uddin, 2024). Additionally, students risk becoming overly reliant on AI, potentially obstructing their critical thinking and problem-solving abilities. Slimi (2023) warns that dependence on AI tools may reduce students' ability to learn independently and engage deeply with course material. Ethical and pedagogical concerns also arise regarding AI's role in education, particularly the risk of AI replacing human educators in key aspects of teaching and mentorship (Galdames, 2024).

Some of the concerns about the integration of AI in education parrot those raised when calculators first made their way into classrooms. Initially, the introduction of calculators sparked hesitation, as the technology was not yet fully understood, nor were teachers confident in its application. There was also uncertainty about how it might impact students. Many educators feared that relying on calculators before mastering basic arithmetic could impede students' ability to retain fundamental mathematical skills. However, as calculators gained widespread acceptance and proved to be an effective tool, educators inevitably adapted to their presence (Banks, 2011).

As educators and institutions incorporate AI into the curriculum many are addressing these challenges by implementing policies and training programs. Universities are developing clear AI policies to regulate ethical AI use, ensuring fairness and data security (Nguyen, 2025). AI ethics courses are being embedded into curricula to educate students about data privacy, bias, and the societal implications of AI (Jose & Jose, 2024). Faculty members receive ongoing training to integrate AI tools responsibly into their teaching practices. Ensuring equitable access to AI technologies for all students, regardless of socioeconomic background, remains a key focus, with institutions working to bridge the digital divide and enhance accessibility for students with disabilities (Nguyen, 2025).

As AI continues to evolve, its role in university studies will likely expand, requiring educators and policymakers to balance innovation with ethical considerations. Future research should focus on refining AI applications in education while addressing concerns related to fairness, transparency, and data security.

AI's Role in Higher Education: Student Perceptions and Decision-Making

Artificial intelligence (AI) has become an increasingly influential tool in higher education, shaping student learning experiences, academic decision-making, and career readiness. Many university students believe that AI should be an integral part of their education, recognizing its potential to enhance learning outcomes and future job prospects (Nguyen, 2025). However, concerns about over-reliance, ethical implications, and disparities in AI literacy continue to shape discussions on AI's role in academia (Holmes et al., 2023).

Research suggests that students value AI for its ability to facilitate personalized learning. AI-driven systems can tailor educational content to individual needs, adjusting to learning pace and style to improve comprehension and retention (Holmes et al., 2023). AI-powered tutoring platforms and adaptive assessments provide immediate feedback, allowing students to refine their academic strategies in real time (Slimi, 2023). These innovations help students grasp complex subjects more effectively, particularly in STEM fields, where AI tools support data analysis, problem-solving, and simulations (Galdames, 2024).

Beyond academic performance, AI also influences student decision-making by providing data-driven insights. AI systems analyze large datasets to generate personalized recommendations for study techniques, course selections, and career pathways, empowering students to make more informed educational choices (Galdames, 2024). AI-driven simulations and decision-making tasks encourage students to engage in higher-order thinking and problem-solving (Nguyen, 2025).

Many students view AI as a valuable addition to their education. A study by Nguyen (2025) found that students appreciate the efficiency gains and innovative potential AI brings to learning environments. However, disparities in AI literacy persist, with many students feeling unprepared to navigate AI's full potential. According to Al Zaidy (2024), only 5% of students reported full awareness of their institution's AI guidelines, while 72% expressed a desire for more AI-related coursework.

Despite its benefits, AI integration presents notable challenges. Over-reliance on AI tools may delay independent learning and critical thinking skills, as students may become dependent on AI-generated responses rather than developing their own analytical abilities (Slimi, 2023). Ethical concerns such as algorithmic bias and data privacy remain critical issues (Uddin, 2024). The perception that peers are more proficient in AI use can also contribute to academic pressure and self-doubt (Kim et al., 2025).

A study by Gerlich (2025) found a significant negative correlation between frequent AI tool usage and critical thinking abilities. Similarly, Basha (2024) highlighted that over-reliance on AI can impede the development of foundational skills, critical thinking, and problem-solving abilities.
To address these concerns, universities are improving AI literacy through structured educational programs and policy frameworks. Institutions are embedding AI ethics into curricula, training faculty to integrate AI responsibly, and ensuring equitable access to AI tools (Nguyen, 2025). Educators emphasize human-AI collaboration, ensuring that AI complements rather than replaces traditional learning methods (Jose & Jose, 2024).

PROBLEM STATEMENT

The integration of artificial intelligence (AI) in education is rapidly evolving, impacting students' learning experiences, decision-making, and academic efficiency. While AI tools offer significant advantages, such as improved learning outcomes and efficiency, they also present challenges, including privacy concerns, limitations in application, and the need for adequate training. Despite the growing role of AI in education, there is a need to assess students' perspectives on its benefits, challenges, and appropriate implementation across various disciplines. Understanding these perspectives will help educators and institutions develop strategies for AI integration that enhance learning while addressing concerns about reliance, critical thinking, and ethical considerations.

HYPOTHESIS AND NULL HYPOTHESES

Hypothesis (H_1 - Alternative Hypothesis):

The integration of AI in education significantly enhances students' learning experiences, decision-making, and academic efficiency, while also presenting challenges such as privacy concerns, over-reliance, and the need for better training.

Null Hypotheses (H_0):

1. H_{01}: The use of AI in education does not significantly improve students' learning experiences, decision-making, or academic efficiency.

2. H_{02}: Students do not perceive significant challenges, such as privacy concerns, over-reliance, or lack of training, in integrating AI into their studies.

3. H_{03}: The presence of AI in education does not have a measurable effect on students' critical thinking, engagement, or learning across different academic disciplines.

These hypotheses will help guide the research by examining the impact, benefits, and challenges of AI integration in education.

Research Questions

1. How do students perceive the benefits and limitations of AI in their studies, and what factors influence their adoption of AI tools?

2. What are the primary challenges students face when integrating AI into their academic work, including concerns about privacy, security, and reliance on AI?

3. How does the use of AI in education impact students' critical thinking, decision-making, and engagement across different academic disciplines?

METHODOLOGY

Students in health and wellness classes were surveyed about their experiences with and attitudes toward artificial intelligence (AI). Participants were asked to rate 15 statements using a four-point

Likert scale: *Strongly Disagree, Disagree, Agree, Strongly Agree,* and *Unknown/Uncertain.* The survey statements are found in Table 5.

The collected responses were analyzed using ChatGPT (OpenAI, 2023) to identify trends and patterns in student perceptions and for hypothesis testing. A t-test was conducted to determine whether the differences in responses were statistically significant.

RESULTS

The statistical analysis explores the significance of student perceptions regarding AI in education. T-tests were conducted to determine whether student responses significantly deviated from a neutral position. The results highlight key insights into students' AI adoption, the benefits and limitations they experience, and the concerns they hold regarding AI implementation in education. Significant findings demonstrate student agreement with AI's role in improving learning efficiency while also acknowledging privacy and usability concerns. Mixed responses in certain areas indicate ongoing uncertainties about AI's future role and its effectiveness across academic disciplines.

The subsequent sections will provide a detailed breakdown of demographic statistics and hypothesis testing results, offering a comprehensive perspective on the integration of AI in higher education.

Descriptive Statistics: Demographics Report

A total of 38 students responded to the survey. The following tables summarize key demographic characteristics, including gender distribution, age statistics, major categories, and academic standing.

TABLE 1: GENDER STATISTICS

Gender	Count
Male	11
Female	18
Other	3
Total Responded	32

This table presents the gender distribution among the 32 students who provided their gender identity. The table includes counts for students who identified as male, female, and other, along with the total number of responses received.

TABLE 2: AGE STATISTICS

Statistic	Value
Minimum Age	18.0
Maximum Age	24.0
Average Age	19.76

This table summarizes the age distribution of the students who participated in the survey. It includes the minimum and maximum ages reported, as well as the average age of the respondents.

TABLE 3: MAJORS DISTRIBUTION

Major Category	Count
Undecided	5
Business	2
Healthcare	10
Science & Technology	11
Fine Arts & Humanities	5
Social Sciences	5
Education	0

This table displays the distribution of students across various major categories. The table includes the number of students in each category, showing that Science & Technology and Healthcare have the highest enrollment, while no students reported being in the Education category.

TABLE 4: YEAR IN SCHOOL

Year in School	Count
Freshman	23
Sophomore	11
Junior	2
Senior	0
Total Responded	36

This table provides a breakdown of students based on their academic year. Among the 36 students who provided this information, the majority were freshmen, followed by sophomores. Only two students were juniors, and no seniors were reported.

Inferential Statistics

T-tests were used for hypothesis testing and to evaluate statistical significance. The t-test results are displayed for each of the 15 statements, assessing whether their mean significantly differs from a neutral value of 2.0. The T-Statistic represents the difference between the sample mean and 2.0, while the P-Value determines statistical significance. Typically, a p-value less than 0.05 suggests a significant difference, indicating that the statement's mean is unlikely to have occurred by chance.

TABLE 5: T-TEST RESULTS

	t-statistic	p-value
1. I use AI tools in my studies or coursework.	2.633913438213190	0.01224978994370850
2. AI technology is frequently integrated into my studies.	-0.9726369966604850	0.3370498299660710
3. AI provides benefits in my education, such as improving efficiency and learning outcomes.	6.28203223231253	2.60863403535201E-07
4. I have encountered challenges or limitations when using AI in my academic activities.	3.340468553770590	0.0019198529595327300
5. AI impacts my understanding and decision-making in my studies.	-1.0000000000000000	0.32380587235541800
6. AI has significantly improved my learning experience.	-0.8820642738358530	0.38343674376445000
7. I have received training or preparation for integrating AI tools into my studies.	2.058050624898530	0.04668088322613000
8. AI will play a growing role in the future of education.	0.4601424174634080	0.6481067851704170
9. I have concerns about privacy and security in relation to AI use in education.	2.2956663052621200	0.02746092747241220
10. AI tools available for students could be improved.	2.051726306875100	0.04732399873214020

11. My peers frequently use AI in studying topics.	-3.2222222222222200	0.0026539737026448700
12. AI should be an integral part of education for students.	-0.1580604932101700	0.8752686378834310
13. AI is used across different academic disciplines to enhance my learning experience.	0.4328908466198210	0.6676071089579400
14. I balance the use of AI with critical thinking and judgment in my coursework.	3.4029207755554700	0.001614928366313090
15. Certain areas within my studies should not rely on AI applications.	8.453570674150490	3.6219538212826E-10

Based on the t-test results, here are key interpretations for each statement:

Statement 1, "I use AI tools in my studies or coursework," has a t-statistic of 2.63 and a p-value of 0.012, which is below the standard significance level of 0.05. This indicates a statistically significant difference from the neutral/disagree response of 2. The positive t-statistic suggests that participants tend to agree more than disagree with this statement, implying that AI tools are commonly used by students in their academic work.

Statement 2, "AI technology is frequently integrated into my courses," has a t-statistic of -0.97 and a p-value of 0.337, which is greater than 0.05. This suggests that there is no statistically significant difference from the neutral/disagree response of 2, indicating that opinions on AI integration in courses are mixed or neutral.

Statement 3, "AI provides benefits in my education, such as improving learning efficiency," shows a t-statistic of 6.28 and a p-value of 0.0000002608, which is well below 0.05. The extremely low p-value indicates a highly significant difference, and the high positive t-statistic suggests strong agreement among participants that AI provides benefits in education.

Statement 4, "I have encountered challenges or limitations when using AI in my studies," has a t-statistic of 3.34 and a p-value of 0.0019, both of which indicate a statistically significant difference from 2. The positive t-statistic suggests that students tend to agree that they have faced challenges while using AI in their studies.

Statement 5, "AI impacts my understanding and decision-making in education," presents a t-statistic of -1.00 and a p-value of 0.324, which is greater than 0.05. This implies that there is no statistically significant difference from neutral, meaning students are divided or uncertain about AI's impact on their understanding and decision-making.

Statement 6, "AI has significantly improved my learning experience," has a t-statistic of -0.88 and a p-value of 0.383, which is above 0.05. This suggests that there is no statistically significant

difference, indicating that students are generally neutral or divided on whether AI has significantly improved their learning experience.
Statement 7, “I have received training or preparation for using AI in my studies,” has a t-statistic of 2.06 and a p-value of 0.047, which is slightly below 0.05. This indicates a statistically significant difference from 2, and the positive t-statistics suggest that students tend to agree that they have received training or preparation for using AI.

Statement 8, “AI will play a growing role in the future of education,” has a t-statistic of 0.46 and a p-value of 0.648, which is well above 0.05. This suggests no statistically significant difference, meaning that students do not overwhelmingly agree or disagree on AI’s future role in education.

Statement 9, “I have concerns about privacy and security in relation to AI use,” has a t-statistic of 2.30 and a p-value of 0.027, which is below 0.05. This indicates a statistically significant difference, and the positive t-statistics suggest that students agree that they have concerns regarding privacy and security in relation to AI use.

Statement 10, “AI tools available for students could be improved for better usability,” has a t-statistic of 2.05 and a p-value of 0.047, which is just below 0.05. This shows a statistically significant difference, and the positive t-statistic suggests that students tend to agree that AI tools could be improved for usability.

Statement 11, “My peers frequently use AI in studying topics,” has a t-statistic of -3.22 and a p-value of 0.0027, which is below 0.05. The statistically significant negative t-statistic suggests that students tend to disagree with this statement, meaning they do not frequently see their peers using AI for studying.

Statement 12, “AI should be an integral part of education in the future,” has a t-statistic of -0.16 and a p-value of 0.875, which is far above 0.05. This indicates no statistically significant difference from neutral/disagree, suggesting that students have mixed or neutral opinions on whether AI should be an integral part of education in the future.

Statement 13, “AI is used across different academic disciplines in my institution,” has a t-statistic of 0.43 and a p-value of 0.668, both of which indicate no statistically significant difference. This means that students do not strongly agree or disagree with the idea that AI is widely used across different academic disciplines.

Statement 14, “I balance the use of AI with critical thinking and independent learning,” has a t-statistic of 3.40 and a p-value of 0.0016, showing a statistically significant difference. The positive t-statistic suggests that students tend to agree that they balance AI use with critical thinking and independent learning.

Statement 15, “Certain areas within my studies should not rely on AI tools,” has a t-statistic of 8.45 and a p-value of 0.000000000362, which is extremely low, indicating a highly significant difference from 2. The high positive t-statistic suggests that students strongly agree that certain areas of study should not rely on AI tools.

DISCUSSION

Overall, the data indicates that while students see AI as beneficial, their views on its role, effectiveness, and limitations remain varied. There is strong agreement on AI's usefulness and areas for improvement but also concerns about privacy and an acknowledgment that AI should not replace essential human-driven aspects of learning.

The findings indicate that students largely acknowledge the role of AI in their studies, with Statements 1, 3, and 4 showing statistically significant differences. Students generally agree that they use AI tools in their coursework, benefit from AI in enhancing learning efficiency, and face certain challenges when integrating AI into their studies. This aligns with previous research emphasizing AI's role in improving engagement and academic outcomes (Holmes et al., 2023; Kilianova et al., 2025).

Conversely, Statements 2 and 5 did not show significant differences, implying that students hold mixed or neutral views regarding AI's integration into their courses and its impact on their decision-making processes. This lack of consensus suggests that while AI has a presence in education, its role and effectiveness vary depending on how it is used in different academic settings, as noted in previous studies (Nguyen, 2025).

Further analysis of Statements 6 to 10 reveals notable areas of agreement and neutrality. Students agree that they have received some level of training in AI use (Statement 7), express concerns about privacy and security (Statement 9), and believe AI tools could be improved for usability (Statement 10). However, their views are more divided when it comes to whether AI has significantly improved their learning experience (Statement 6) and its potential future role in education (Statement 8). These mixed reactions highlight that while AI has demonstrated benefits, it is not yet universally regarded as an essential or flawless tool in education, echoing concerns about ethical and pedagogical implications (Slimi, 2023; Uddin, 2024).

The results from Statements 11 to 15 provide additional insights into students' perceptions of AI use. Students disagree that their peers frequently use AI in studying (Statement 11), indicating that while AI adoption is growing, it may not yet be widespread among their classmates. Additionally, students remain neutral on whether AI should be an integral part of education (Statement 12) and whether it is widely used across academic disciplines (Statement 13). However, they agree that they balance AI use with critical thinking and independent learning (Statement 14) and strongly agree that certain areas of study should not rely on AI tools (Statement 15). This suggests that students recognize AI as a useful but limited tool, reinforcing the importance of human reasoning and subject-specific considerations when integrating AI into education (Jose & Jose, 2024; Nguyen, 2025).

Overall, the data indicates that while students see AI as beneficial, their views on its role, effectiveness, and limitations remain varied. There is strong agreement on AI's usefulness and areas for improvement but also concerns about privacy and an acknowledgment that AI should not replace essential human-driven aspects of learning. This reflects prior literature highlighting both the advantages and challenges of AI in education and the need for responsible AI integration (Nguyen, 2025; Holmes et al., 2023).

Findings in Relation to the Problem Statement, Research Questions, and Hypothesis Testing

The findings indicate that students largely acknowledge the role of AI in their studies, with statistically significant differences observed in Statements 1, 3, and 4. These results suggest that AI is perceived as beneficial for learning efficiency and decision-making, aligning with the research problem's emphasis on AI's role in improving education while presenting certain challenges.

Regarding the research questions, students' perceptions of AI's benefits and limitations align with the findings that many students use AI tools in their coursework and find them useful for academic efficiency. However, challenges such as privacy concerns and the need for better training (Statements 7 and 9) underscore the importance of addressing barriers to AI adoption. These results confirm that while AI enhances education, there are critical issues to resolve, supporting Research Question 1.

In response to Research Question 2, the study highlights primary challenges students face, including data privacy and AI reliance. The findings show that students recognize the importance of balancing AI use with independent learning (Statement 14) and that AI tools require improvements for usability (Statement 10). This supports the notion that AI integration must be managed carefully to avoid over-reliance while ensuring data security and ethical use.

With regard to Research Question 3, the results indicate mixed perceptions about AI's impact on critical thinking and engagement. Some students express concerns about AI's role in learning and decision-making (Statement 6), while others acknowledge AI's benefits in enhancing engagement in specific academic settings (Statement 8). These findings suggest that AI's impact varies depending on discipline and its application, reinforcing the need for targeted AI policies in different fields of study.

The findings also provide insight into hypothesis testing. The significant differences in students' agreement with Statements 1, 3, and 4 support the alternative hypothesis (H_1), indicating that AI does improve learning efficiency and decision-making. However, the mixed responses in Statements 6, 8, and 12 suggest that AI's effect on critical thinking and engagement is not universally agreed upon, aligning with H_{03}, which posits that AI's presence in education does not have a measurable effect on critical thinking across disciplines. Similarly, the concerns about privacy and AI over-reliance confirm that students perceive challenges in AI adoption, rejecting H_{02}.

CONCLUSION

The integration of artificial intelligence (AI) in higher education has generated widespread interest, with students and educators recognizing both its potential benefits and associated challenges. AI has proven to be a valuable tool for personalized learning, data-driven decision-making, and efficiency in various academic disciplines. While AI adoption is more readily accepted in STEM and business fields, students in the humanities, social sciences, and creative arts express concerns about ethical implications, bias, and the preservation of human judgment and creativity.

Many university students believe that AI should be an integral part of their education, acknowledging its ability to improve educational outcomes and prepare them for future careers (Nguyen, 2025). However, ensuring that students are equipped with AI literacy, ethical guidelines, and opportunities for human-AI collaboration will be key to maximizing the benefits of AI in education while mitigating its potential risks.

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