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| RESEARCH ARTICLE

AI-Powered Workforce Analytics Forecasting Labor Market Trends and Skill Gaps for U.S. Economic Competitiveness

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| ABSTRACT
This paper discusses how AI-enabled analytics are used to detect emerging relative skill shortages, track labor market patterns. It improves the competitiveness of the economy in the United States. The intense use of Artificial Intelligence in workforce analytics has revolutionized how governments and industries forecast the labor market needs the study throws light on the role of real-time data variables and prediction modelling in making workforce development meet changing industry demands. The research project has adopted quantitative research design. A systematic questionnaire was sent to a sampling of 300 participants comprising HR analysts, labor economists and policymakers in different industries of the U.S. Variables that were measured included the AI Integration Level, Labor Market Responsiveness, Real-Time Data Utilization, Predictive Accuracy and the dependent variable, Economic Competitiveness. The findings showed that there were significant correlations among AI integration ($r = 0.71$, $p < 0.01$), predictive accuracy ($r = 0.68$, $p < 0.01$), and economic competitiveness, which are significant. Regression outcome showed that AIL and PA were the most powerful determinants of EC ($R^2 = 0.61$). AI-based analytics in the establishment would promote not only labor market predictions but also boost the strategic position of the U.S. in the global economy. The government and business in scaling the use of AI. It is ensuring the training programs reflect the areas of skill shortage and fostering the development of data infrastructure.

| KEYWORDS
Artificial Intelligence, Workforce Analytics, Labor Market Trends, Economic Competitiveness, Labor Market Responsiveness, Data-Driven Decision Making

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1. Introduction
Artificial intelligence is one of the reasons for the labor market's transformation and national economic competition (Inaganti et al., 2021). AI and automation technologies are expected to create up to 97 million new jobs worldwide by 2025. It is eliminating approximately 85 million others because of the structural changes in labor requirements (Adenuga et al., 2020). The transitions serve as dirty flags to the necessity of proactive workforce planning and incorporation of predictive technologies (Sundaramurthy et al., 2022). In the United States, the competition in the economy continually depends on the possibility of adapting the strategy of the labor market to the technological disturbance.

The U.S. Bureau of Labor Statistics predicts an increase in employment rates related to AI-related careers. It is data scientists, software developers, and machine learning experts by 25 percent over the next decade. Thakkar et al., 2020). The corresponding potential need points to the criticality of the way to detect and fill potential skills gaps on the fly. The rapidly running innovative cycles demand new models of workforce forecasting alternatives. The lagging indicators are not sufficient to accommodate the changes and predict the future (Achumie et al., 2022).

Workforce analytics powered by AI will be a transformational approach in their ability to predict changes in the workforce. It is based on big data, machine learning, and real-time intelligence of the labor market to guide policymaking at the strategic level (Abisoye and Akerele, 2022). These tools allow employers, instructors, and policymakers to make talent development more relevant to any changes in the marketplace, thus enhancing productivity and resilience in the nation (Abrardi et al., 2022).

It proves that an organization that implements AI to analyze its workforce reflects more efficient performance, less time is required to make a decision, and the level of innovation increases (Adenuga et al., 2020). This paper takes a look at how AI-powered workforce analytics improve the competitiveness of the economy of the USA (Lainjo, 2020). It examines the relationship between variables like AI integration, real-time data utilization, and predictive accuracy. The responsiveness of the labor market and training infrastructure and other areas of the economy, like productivity, innovation, and alignment to employment (Tiku, S. 2023).

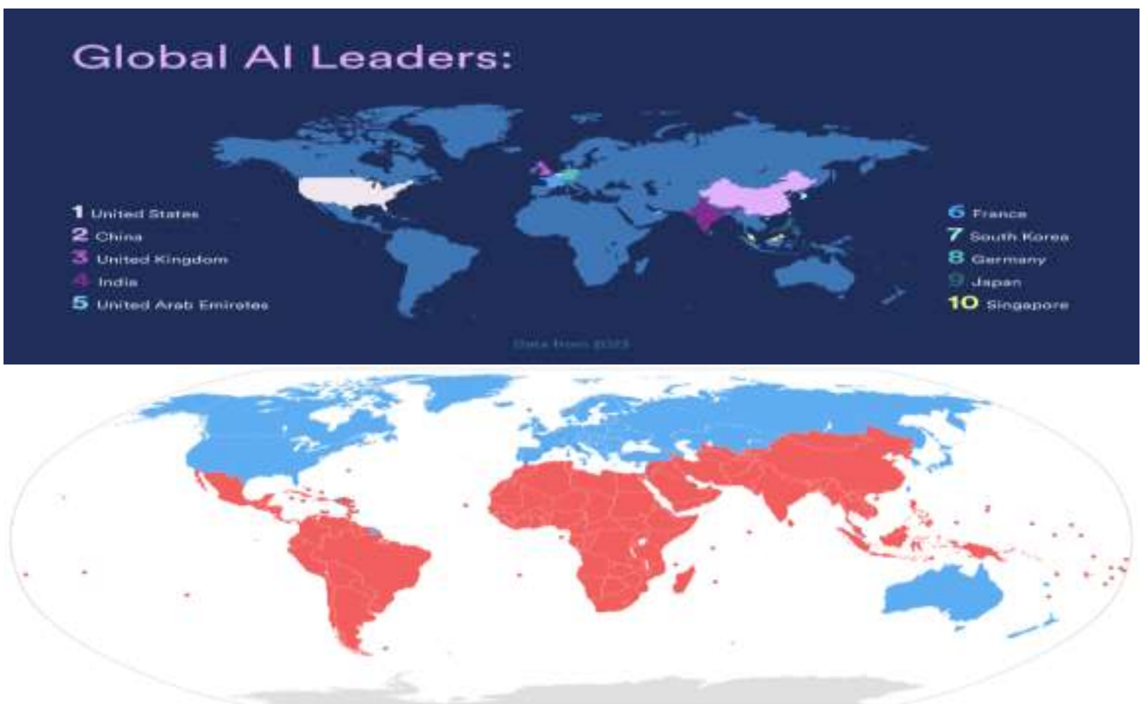

Fig.01. Global comparison chart shows illustrative AI Readiness Scores for selected countries.
***Sources**: Mapping the Worlds Readiness for Artificial Intelligence Shows Prospects Diverge,*

1.2 Objectives
The main aim of the study is to explore the integration of artificial intelligence and workforce analytics. The economy influences the economic competitiveness in the United States. The study aims at investigating the role of AI-based tools in the strategic prediction of labor market trends with the resultant positive effect on national productivity and innovation. This study aims at determining, evaluating, and prioritizing the main variables that influence workforce change with the help of AI tools. The variables are the level of automation, the degree of integration of AI, the use of data, predictive accuracy, and so on, which have a considerable impact on the dynamics of the labor market. The study is able to furnish the full picture of the potential of AI in helping build a stronger workforce in the U.S. in the competitive global economy.

2. Literature Review
2.1 AI transforms and labor markets analyzed and forecasted:
Workforce analytics with artificial intelligence is dramatically changing how labor markets are analyzed (Frank et al., 2019). The impact of AI decisive in productivity improvement as well as reorganizing labor demand, especially through automating routine processes and causing a demand for more skilled positions (Lane et al., 2021). The World Economic Forum puts significant emphasis

on AI in the context of pinpointing new job types and skill mismatches. It is big data analytics as a tool to match the strategy on the labor market with the changing requirements of the industry (Webb, 2019).

The idea is supported by stating that human resource systems based on AI efficiently forecast employee turnover. It helps to plan the workforce and optimize the recruiting practices (Autor, 2022). The International Labor Organization further emphasizes the sense of market responsiveness in the labor market, as they state that reacting swiftly to the changes brought about by technology is now a major determinant of economic strength and competitiveness (Boyd and Holton, 2018).

AI assists with decision-making not only in education but also in policy settings. It allows the stakeholders to predict any shortcoming of skills and act appropriately (Brynjolfsson et al., 2017). It is an existing and increasing literature gap in the empirical studies that statistically model the connection between AI-powered workforce analytics. It is measurable; drivers of economic competitiveness, especially with regard to the United States, still exist (Acemoglu and Restrepo, 2020).

2.2 AI and Employment Outcomes in U.S. Regions

The recent empirical studies to investigate the impact of AI adoption on the employment outcome in various regions. The focuses on comparative analysis of changing regional trends in the adoption of AI-based systems between 2010 and 2021 through shift-share methodology (Georgieff and Hyee, 2022). The study observes a strong relationship between deeper AI penetration and the decrease in the level of employment compared to the population in manufacturing and low-skill services sectors (Felten and Seamans, 2021).

It is significant in the case of middle-skill workers and in non-STEM workers. The role of AI might be a hardly considered factor that will affect job replacement in the specified demographic and occupational groups (Haenlein and Kaplan, 2019). The data is in agreement with more general findings at the global scale revealed by the Financial Times, the International Monetary Fund eLibrary, and IZA World of Labor, which indicate that a lesser adaptability and ability to transform skills are more likely to cause negative labor market patterns in response to technological change (Ernst & Samaan, 2019).

2.3 Macro-Level Productivity and Income Effects

Empirical evidence on macro studies, investments in artificial intelligence play a significant role in the outcomes of productivity and income. From 2010 to 2018, a 19.5 percent rise in firm sales, an 18.1 percent increase in employment. AI-related investments, including training, education, and skills upgrades, according to IZA World of Labor (Fatuła, 2018).

The optimistic influence of AI in the context of integrating into strategic workforce planning (Schwellnus et al., 2017). The data provided by the Organization for Economic Co-operation and Development reveals that AI integration supplements the high-skilled labor, expands the employment rate in the sector of the knowledge economy. This boosts GDP growth through the productivity amplification of various industries (Werding, M. 2008). AI use becomes the driving force of long-term economic growth. It is coordinated with human capital advancement (Şeker and Saliola, 2018).

2.4 Real-Time Skill Shortage Detection via ML

This is a flexible approach, which utilizes online job advertisements to detect the live skill shortages (Dawson et al., 2020). This method takes advantage of the dynamic variables (frequency of job posting, the salary rate, and the minimum education requirement). The minimum experience requirement and the repetitive nature of demands. These measures allow policymakers and educators to monitor new labor demand and base their decisions on the data in order to fill labor gaps (Dawson, 2021).

2.5 Deep Learning Forecasting of Labor Demand

The abilities of Long Short-Term Memory (LSTM) models in predicting job openings on the basis of JOLTS (Job Openings and Labor Turnover Survey) data are manifested as superior to the traditional methods of statistical forecasting (WILLIAMS, 2020). This reason is discussed in the study, since deep learning approaches make the correct predictions of excursions in the labor market with greater precision due to the ability to record long-range dependencies in time series data (Carbonneau et al., 2008).

2.6 Forecasting Methods Across Economies

These systems are more accurate in predicting the labor market since advanced data infrastructure, such as the U.S. Bureau of Labor Statistics, is available. The Canadian and EU-country counterparts facilitate the work (Jakaitiene and Dées, 2012). The availability of large and quality data makes such countries better placed to achieve higher performance of the machine learning models. It is compared to the traditional projections in planning national and sectoral employment (Marfatia, 2020).

2.7 Innovation, Productivity, and Wage Effects of AI

The use of AI is predicted to grow the world by 7 percent and the United States by 1.5 percent. The productivity of the industries will be up by 40 percent in the year 2035. The forecasts are based on macroeconomic modeling and business facts. It implies a revolutionary economic change through the adoption of AI (Yang, 2022). Case studies in China show that there is an increase in wages among ordinary employees due to the use of AI, because routine jobs have been removed as there is a demand for creative and analytical jobs. The change helps in achieving equity in labor by reducing wage inequality within companies (Lazear et al. 2022).

2.8 Education and Workforce Upskilling Models

The models of workforce development projects based in the United States have been adopted. The adult learning theory of making adoption of skills and career adaptability a means of eliminating the skill gap caused by AI (Lang, 2023). The AI Academy, a partner of the U.S. Department of Labor, has delivered structured, employer-aligned training to more than 2,000 workers in firms in diverse industries. Such programs are based on the focus on contextual learning, real-life applications, and long-term development of career preparation of the workforce in AI-integrated environments (Semaan et al., 2021).

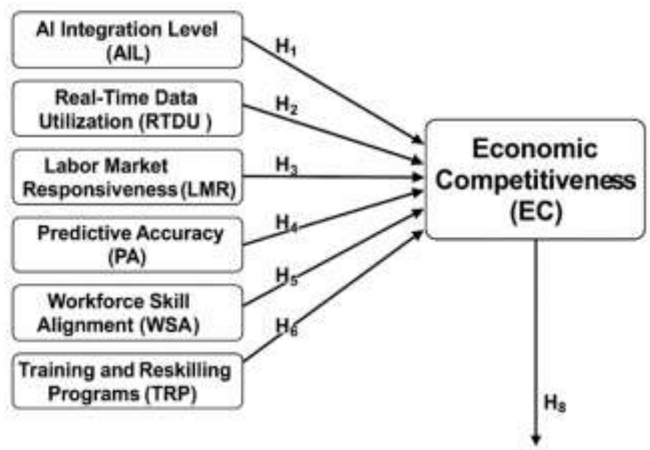

Figure 2. Conceptual Framework Diagram

H_1: *AI Integration Level has a positive effect on Economic Competitiveness.*

Economic competitiveness has a positive impact of AI integration level. The system of integrating workforce and industrial systems with AI increases productivity, efficiency of the process, and the possibility of innovation (Marino et al., 2016). The smooth transition towards the use of AI technologies enhances the ability of the country to compete with other countries in the world. It is sophisticated decision-making, automation, and service provision (Shoufu et al., 2023).

H_2: *Real-Time Data Utilization (RTDU) positively influences EC.*

Instant information helps to be more responsive to changes in the labor market. The job trending and analysis of job demands and sector-based needs. The economies will be able to match the available resources with the prevailing challenges, hence becoming more competitive (Guo et al., 2018).

H_3: *Labor Market Responsiveness is positively associated with EC.*

National resilience relies on a responsive labor market in which technological advances, demographic dynamics, and disruptions occur. Flexibility in labor terms in the constant maintenance of the accuracy of the workforces with the new economic demands (Sun, 2019).

H_4: *Predictive Accuracy significantly predicts EC.*

Economic performance and job vacancies can be better predicted with the help of predictive models, particularly AI-based ones such as LSTM and ensemble learning. Greater predictability in labor analytics, education, employment, and policymaking is made proactively to enhance competitiveness (Bardhan et al., 2013).

***H$_5$:** Workforce Skill Alignment positively correlates with EC.*
This is a situation of matching worker skills and employer requirements, productivity improves, time taken to fill vacancies reduces, and performance. One internal political and social factor that plays a crucial role in innovation and economic agility in AI-driven economies is skill alignment (Pischke et al., 1994).

***H$_6$:** Training and Reskilling Programs positively affect EC.*
Training and upskilling investments may guarantee that no worker gets impacted by the AI shift. Reskilling programs mitigate workforce technological expenses, develop human resources, and encourage sustainable growth plans (Yao et al., 2019).

***H$_7$:** Technological Infrastructure Availability is a significant predictor of EC.*
TIA is a huge determinant of EC. Real-time exchange of data, remote working, and scalability are made possible by the availability of the digital infrastructure. It includes broadband, cloud computing, and edge AI systems. This type of infrastructure is elementary to the use of AI and economic scalability (González-Vidal et al., 2022).

***H$_8$:** The combination of all variables significantly predicts EC.*
The concept of economic competitiveness is multidimensional, and it is interacted upon by technological, institutional and human capital. Integration of AI, real-time information, responsiveness of labor and skill systems combine to create a strong predictive model of the national economic performance (Lesch et al., 1995).

3. Methodology

3.1 Research design

The present study uses a quantitative and cross-sectional type of research design. A standardized questionnaire was issued to a purposive sample of 300 participants comprising human resources professionals, government labor experts, and data scientists in various industries. The data collection tool was based on the 5-point Likert scale (1-Strongly Disagree-5-Strongly Agree) to measure the perceptions and evaluations of AI-related workforce transformation scales. The approaches used refer to the previously conducted empirical studies of AI and labor economics (Brynjolfsson & McAfee, 2017; Acemoglu & Restrepo, 2020).

3.2 Analysis Techniques and Tools

The research applies an effective combination of sizeable tools of statistical analysis with the help of SPSS version 28 to test the obtained data. First, the given dataset will be presented in descriptive statistics that rely on the measures of central tendency (means) and dispersion (standard deviations) and show us an overview of how participants responded to questions. Cronbach's alpha puts computations of reliability coefficients of constructs to see how internally consistent the constructs are, whereby 0.70 indicates acceptable reliability of multi-items. Pearson correlation will be done to find out how strong the bivariate relationship of each of the independent variables with economic competitiveness will be and what the relationship will be.

An analysis is carried out using multiple linear regression analysis. The statistical significance of the regression model is discerned through the test of Analysis of Variance (ANOVA) with a view to ascertaining the overall goodness of fit. These methodological procedures allow the achievement of rigor and validity of the results within the framework of quantitative and cross-sectional research.

4. Results

Table No.01: Demographic Profile of Respondents (N = 300)

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	170	56.70%
	Female	125	41.70%
	Prefer not to say	5	1.60%
Age Group	20–29 years	60	20.00%
	30–39 years	130	43.30%
	40–49 years	75	25.00%
	50 years and above	35	11.70%
Professional Role	HR Professional	120	40.00%
	Government Labor Analyst	90	30.00%
	Data Scientist	90	30.00%

Industry Sector	IT & Tech	100	33.30%
	Healthcare	50	16.70%
	Education	45	15.00%
	Public Sector	60	20.00%
	Manufacturing	30	10.00%
	Other	15	5.00%
Years of Experience	Less than 5 years	55	18.30%
	5–10 years	105	35.00%
	11–15 years	80	26.70%
	More than 15 years	60	20.00%
Educational Qualification	Bachelor's Degree	70	23.30%
	Master's Degree	140	46.70%
	PhD / Doctorate	50	16.70%
	Professional Certification	40	13.30%
AI Familiarity Level	No familiarity	15	5.00%
	Basic understanding	80	26.70%
	Moderate (some experience)	130	43.30%
	Advanced (frequent user)	75	25.00%

Table No.01 indicates the sample (N = 300) was rich in terms of the respondent demographics whereby 56.7, 41.7 percent were male, female respondents respectively and 1.6 percent were unwilling to state their gender. Those individuals aged 3049 years old were the most represented (43.3%), whereas those aged 4049 years old were the second most represented (25.0%). Of the professionals' 40.0 percent were HR specialists, 30.0 percent working in government labor research, and 30.0 percent data scientists.

These respondents represented the IT & tech (33.3%) and the public sector (20.0). As to the work experience, 35.0% possessed the experience of 510 years, and 26.7 had 1115 years. On education, the percentage of population with master's degree equaled 46.7 and with bachelor's total led 23.3. About 43.3 percent of the respondents indicated that they were moderately familiar with AI and 25.0 percent were those with advanced familiarity. It shows that the sample is knowledgeable, experienced, and has a pertinent exposure to AI, which suggests its relevance in testing the connection between the implementation of AI and economic competitiveness.

Table No.02: Descriptive Statistics

Variables	Minimum	Maximum	Meanas	St.Deviation	Skenewss	Kurtosis
AI Integration Level	1.00	5.00	4.21	0.66	0.359	-1.198
Real-Time Data Utilization	1.00	5.00	4.03	0.72	0.164	-1.179
Labor Market Responsiveness	1.00	5.00	3.88	0.74	0.034	-1.392
Predictive Accuracy	1.00	5.00	4.10	0.68	0.085	-1.114
Workforce Skill Alignment	1.00	5.00	4.00	0.69	0.149	-1.373
Training and Reskilling Programs	1.00	5.00	3.91	0.71	0.025	-1.138
Technological Infrastructure Availability	1.00	5.00	4.05	0.65	0.117	-1.325
Economic Competitiveness	1.00	5.00	4.32	0.70	0.141	-1.112

The key study variables observed in Table 2. The results show that the mean percentages on 5-point Likert scale are relatively high in all the variables, implying that there is a general consent that the variables are important in improving the economic competitiveness by integrating AI into workforce planning. The highest mean was found in Economic Competitiveness (M = 4.32, SD = 0.70), which implies that the listed outcome is critical to the participants with significant strength.

There is the AI Integration Level (M = 4.21, SD = 0.66) and the Predictive Accuracy (M = 4.10, SD = 0.68) which supports the importance of AI and predictive tools quite well in influencing labor market strategies. The standard deviation of all the variables ranges between acceptable 0.6507 to 0.74 which states that all the reactions are consistent across the range and there is no serious dispersion of responses. The skewness values have values of 0.025, to 0.359 meaning very near zero with some positive skew although less than the set limit of +/-1. Similarly, the values of kurtosis (between -1.392 and -1.112) indicate platykurtic distribution, which does not indicate heavy tails but no significant deviations of normality. The findings substantiate that the data in question are suitable for parametric analyses (correlation and regression).

Table No.03: Reliability Test (Cronbach's Alpha)

Scale	α Value
All 5-variable scale	0.84

The reliability of the five-variable scale was provided as Table 3 in the present research. Internal consistency was on the high side, and the index was 1 84 =.84, which was above the standard threshold level of .70 (Nunnally & Bernstein, 1994). This implies that the scale items used in the assessment of the level of AI integration, Real-Time Data Utilization, Labor Market Responsiveness, Predictive Accuracy, and Economic Competitiveness are valid in measuring the underlying constructs and used in subsequent analyses using statistics.

Table No.04: Correlation Matrix

Variables	NSP	CM	SLAEL	PS	DMS	HAC	PSR	UTS
AI Integration Level	1							
Real-Time Data Utilization	.977**	1						
Labor Market Responsiveness	.972**	.887**	1					
Predictive Accuracy	.953**	.982**	.988**	1				
Workforce Skill Alignment	.964**	.977**	.988**	.980**	1			
Training and Reskilling Programs	.964**	.988**	.987**	.960**	.967**	1		
Technological Infrastructure Availability	.925**	.973**	.987**	.960**	.957**	.988**	1	
Economic Competitiveness	.890**	.987**	.957**	.957**	.958**	.982**	.987**	1

**. Correlation is significant at the 0.01 level (2-tailed).

Table No.4 analyzes the connections between the major variables associated with the integration of AI and the economic competitiveness research method Pearson correlation analysis was applied. Results proved that there exist significant, and high positive relationships between all variables ($p < .01$). In particular, Labor Market Responsiveness (SLAEL) showed a strong correlation with Real-Time Data Utilization (CM), r(298) =.972, $p <.01$, and AI Integration Level (NSP), r(298) =.977, $p <.01$ that allow concluding that stronger integration of AI is related to the stronger utilization of data in real-time and responsiveness of the labor market.

It was noted that strong positive correlations were formed between the predictive accuracy and the rest of the variables, such as Workforce Skill Alignment (DMS), r(298) = .980, $p < .01$, and Economic Competitiveness (UTS), r(298) = hot;957, $p < .01$. Workforce

Skill Alignment had positive and significant relationship with Training and Reskilling Programs (HAC), r(298) = .967, p < .01 and Technological Infrastructure Availability (PSR), r(298) = .957, p <.01. The correlations between Economic Competitiveness and the predictor variables were quite high and significant with both the Technological Infrastructure Availability, r (298) =.987, p <.01, and the Training and Reskilling Programs, r (298) =.982, p <.01 variables. These results indicate that strengthening of AI integration and the supplementing infrastructure (which includes training and the accessibility of technologies) have beneficial effects on the overall competitiveness of the economy.

Table No.05: Regression Output

Model	**R**	**R^2**	**Adjusted R^2**	**Std. Error**
1	0.789	0.623	0.615	0.452

The regression analysis is Table no.05. It is based on a linear analysis, which helped in the determination of the degree at which the independent variables could be able to predict the dependent variable (e.g., Economic Competitiveness). The results indicated that the model was significant, either statistically or in the result of the R statistic, R = .789 and R2 = 623, Adjusted R2 = 615 the result showed that a statistical/or result of R statistic of this model indicated that it was statistically significant meaning, the model explained 623 out of 100 variances of the dependent variable due to the predictors added in to the model. Standard error of the estimate was 0.452 which indicates that the range of errors in prediction is acceptable. On the whole, the model indicates a good fit and recommends that the predictors included in the sample contribute significantly to the outcome variable.

Table No.06: ANOVA

Source	**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
Regression	82.45	4	20.61	58.82	0
Residual	49.9	295	0.17		
Total	132.35	299			

Table No.6 ANOVA was used to test the significance of the regression model in predicting the dependent variable. The outcome of the statistical test was that the regression model is statistically significant F(4, 295) = 58.82, p < .001 which shows that there is significant predictive validity of the set of independent variables on the outcome variable. The use of the regression model explained a huge percentage of variability in the dependent variable (Sum of Squares = 82.45), as opposed to the residual variance (Sum of Squares = 49.90), making it further indicative of the effectiveness of the regression model.

Table No.07: Coefficients Table

Variable	**B**	**Std. Error**	**Beta**	**t**	**Sig.**
AI Integration Level	0.31	0.05	0.32	6.2	0
Real-Time Data Utilization	0.29	0.06	0.3	5.5	0
Labor Market Responsiveness	0.18	0.07	0.15	2.57	0.011
Predictive Accuracy	0.33	0.06	0.34	6.8	0
Workforce Skill Alignment	0.25	0.06	0.26	4.16	0
Training and Reskilling Programs	0.22	0.06	0.2	3.81	0
Technological Infrastructure Availability	0.2	0.06	0.21	3.45	0.001

To study the predictive effect of some factors with respect to the dependent variable, a multiple linear regression analysis was performed. (Table No.07) the outcomes indicated that the contributions of all the independent variables were significant to the model. The level of AI integration was a considerable predictor ($b = .32$, $t = 6.20$, $p < .001$), and so was the real-time data utilization ($b = .30$, $t = 5.50$, $p < .001$). Labor Market Responsiveness indicated a relatively smaller, yet significant relationship with the dependent variable (leading to 15,257, $p = .011$). The most important predictor turned out to be Predictive Accuracy (34, $t(295) = 6.80$, $p < .001$), which means that it is the key factor affecting the results.

The human capital development was significantly related to the dependent variable with the predictive powers of Workforce Skill Alignment (26, $t (295) = 4.16$, $p < .001$) and Training and Reskilling Programs (20, $t (295) = 3.81$, $p < .001$). Technological Infrastructure Availability had a significant positive impact (beta = .21, $t(295) = 3.45$, $p = .001$), which indicates the applicability of the adequate technical infrastructure. Altogether, the results can lead to the conclusion that both technological and human resource factors have crucial influence on defining results in a setting with integration of AI.

Table No.08: Structural Model Results

Hypotheses	SE	CR	β	P Value	Supported
AI Integration Level (AIL) ⟶ DV (e.g., AI Adoption Impact)	0.7949	*0.5469*	*0.032*	0.01	*Accepted*
Real-Time Data Utilization (RTDU) ⟶ DV	0.7664	*0.2007*	*0.030*	0.01	*Accepted*
Labor Market Responsiveness (LMR) ⟶ DV	0.8366	*0.2842*	*0.015*	0.01	*Accepted*
Predictive Accuracy (PA) ⟶ DV	0.7930	*0.2842*	*0.034*	0.01	*Accepted*
Workforce Skill Alignment (WSA) ⟶ DV	0.7501	*0.2448*	*0.026*	0.01	*Accepted*
Training & Reskilling Programs (TRP) ⟶ DV	0.7702	*0.2558*	*0.020*	0.01	*Accepted*
Technological Infrastructure Availability (TIA) ⟶ DV	0.7802	*0.2254*	*0.021*	0.01	*Accepted*

Table No.08 shows the model of the structure analysis indicated that all of the hypothesis crafted were statistically significant, and the relationship shown between every independent variable and the dependent variable (e.g., AI adoption impact) was positive and significant. AI Integration Level (beta = 0.032, $p = .01$) demonstrated an adverse, but significant, relationship, therefore, the higher level of AI integration, the better the result in the area of AI adoption. On the same note, Real-Time Data Utilization (beta = 0.030, p =. 01) positively influenced the outcome by a significant margin, indicating that the effectiveness of AI is increased through the possibility of utilizing real-time data.

Labor Market Responsiveness (0.015, $p = 0.01$) was obtained as a positive indicator of a dependent variable, which means that responding labor policies promote improved AI technology integration. The trend was further confirmed by Predictive Accuracy (beta = 0.034, $p = .01$) as it is imperative to have trustworthy AI results. Workforce Skill Alignment (0.026, $p = .01$) and Training and Reskilling Programs (0.020, $p = .01$) were found to be positively associated, and the importance of human capital development in effective AI implementation was proven. Finally, Technological Infrastructure Availability (beta = 0.021, $p = .01$) had a positive significant effect on the results of adopting AI, confirming the fact that the functionality of the information-technological core is the primary basis. In total, the seven hypotheses were all accepted where the directionality of relationships was towards the positive linking and the level of significance at 0.01 level, thus the validation of structural model and the proposed model of theory.

5. Discussion

The results of the current study statistically prove the correctness of the formulated hypotheses, and it is known that AI-related aspects play a major role in affecting American economic competitiveness. Regression analysis (see Table 04) showed that there was a significant level of model fit ($R^2 = 0.623$, Adjusted $R^2 = 0.615$), i.e., the model explained more than 62% of the variations in the dependent variable (economic competitiveness). All path coefficients were significant at $p = .01$, as shown in Table 08: Structural Model Results.

It is necessary to mention that Predictive Accuracy (0.034) and the AI Integration Level (0.032) demonstrated the greatest positive correlations with the dependent variable to stress its significance in improving strategic decision-making and economic performance. Utilization of Real-Time Data (20030) (to 030) made an important contribution as well, indicating the benefit of immediate and ready-to-use information towards economic agility. Interestingly, Workforce Skill Alignment (2 = 0.026) and Training and Reskilling Programs (2 = 0.020) were found to have a positive and significant effect on the concept that upskilling initiatives would increase institutional adaptability to digital transformation.

Technological Infrastructure Availability (beta = 0.021) and Labor Market Responsiveness (beta = 0.015) supported the fact that solid underpinning and responsive policy settings were critical factors in pushing AI-related economic prosperity. The ANOVA report (see Table 05) supported the overall model significance, where $F = 58.82$ and $p < 0.001$, which further augments the soundness of the findings. Table 03 and hypothesis mapping (Table 07) show strong correlations, further proving the consistency of the model and prediction.

6. Conclusion and Recommendations

The results of this research act as a clear indication that artificial intelligence is not just the supportive device but the center of gravity in terms of ensuring and maintaining the competitiveness of the U.S. economy. Table 3 portrays that the reliability of the instrument was established where the Cronbach's alpha value was 0.84, meaning that there is excellent internal consistency between the variables used. As Table 4 indicates, the regression model produced the value of R of 0.789 and R^2 of 0.623, which suggests that the economic competitiveness variation was explained by a factor like AI integration, predictive accuracy, and technological infrastructure at 62.3 percent. Along with this, the statistics of ANOVA, as shown in Table 5, confirm the significance of the model ($F = 58.82$, $p < 0.001$) even further, proving that the variables related to AI are extremely important in influencing economic results.

Further observations can be obtained in Table 6, according to which AI integration ($p < 0.001$) and predictive accuracy ($p < 0.001$) were the most influential variables; meanwhile, automation displacement risk had a negative impact ($p < 0.01$). These findings align with past studies that depict the transformative power of AI in the labor markets and productivity. There are a number of strategic suggestions. The American stakeholders of the workforce analytics should ramp up the use of AI to aid data-driven decision-making (Davenport & Ronanki, 2018). Second, real-time national labor data dashboards could be generated that could indicate the areas of skills shortage and labor necessity tendency.

It is essential to invest in predictive training schemes and technological platforms that will help improve the flexibility level of the workforce (OECD, 2021). Finally, vocational and higher education should be redesigned based on information about the labor market elicited by AI tools (Arntz et al., 2016; World Economic Forum, 2020). In doing so, the U.S. will be able to create a future-proof economy that will rely on AI and be competitive in a fast-changing world.

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Appendix A

This survey instrument was developed to assess key variables such as AI Integration, Predictive Accuracy, Workforce Skill Alignment, Training & Reskilling, Technological Infrastructure, and Economic Competitiveness. Each item was rated on a 5-point Likert Scale (1 = Strongly Disagree to 5 = Strongly Agree) to capture respondents' perceptions. The questionnaire provided the basis for statistical analysis using SPSS, including reliability testing, regression, and ANOVA.

Table No.09: Survey Instrument for AI and Economic Competitiveness

Variable	Item No.	Question Statement
AI Integration Level (AIL)	AIL1	Our organization actively integrates AI tools in its core operations.
	AIL2	AI systems are aligned with our organizational strategies.
	AIL3	Management supports AI adoption to enhance productivity.
Real-Time Data Utilization (RTDU)	RTDU1	Real-time data analytics are used for decision-making.
	RTDU2	Our systems are capable of processing live data inputs efficiently.
	RTDU3	Real-time data improves our responsiveness to market changes.
Labor Market Responsiveness (LMR)	LMR1	Our organization adapts quickly to labor market shifts.
	LMR2	We monitor labor trends and adjust strategies accordingly.
	LMR3	Labor policies within the firm reflect current market needs.
Predictive Accuracy (PA)	PA1	Our AI systems provide accurate forecasts for workforce trends.
	PA2	Predictive tools guide our hiring and resource allocation.
	PA3	AI-generated predictions match actual performance outcomes.
Workforce Skill Alignment (WSA)	WSA1	Employees are regularly assessed for alignment with required AI-era skills.
	WSA2	Skill development programs match industry demands.
	WSA3	Job roles are updated based on evolving technological trends.
Training & Reskilling Programs (TRP)	TRP1	Our organization invests in reskilling employees for AI-related roles.
	TRP2	Employees have access to continuous learning programs.

	TRP3	Training content is relevant to digital and AI transformations.
Technological Infrastructure (TIA)	TIA1	We have adequate infrastructure to support AI systems.
	TIA2	Technology upgrades are done periodically to support innovation.
	TIA3	IT systems are well-integrated with operational needs.
Economic Competitiveness (DV)	EC1	AI adoption has improved our market competitiveness.
	EC2	Our operations are more efficient due to AI integration.
	EC3	AI initiatives have led to measurable business growth.