Journal Pre-proof

Global Adoption of Generative AI: What Matters Most?

Hassnian Ali, Atta ul Mustafa, Ahmet Faruk Aysan

Please cite this article as: Hassnian Ali, Atta ul Mustafa and Ahmet Faruk Aysan, Global Adoption of Generative AI: What Matters Most?, *Journal of Economy and Technology*, (2024) doi:https://doi.org/10.1016/j.ject.2024.10.002

This is a PDF file of an article that has undergone enhancements after acceptance, such as the addition of a cover page and metadata, and formatting for readability, but it is not yet the definitive version of record. This version will undergo additional copyediting, typesetting and review before it is published in its final form, but we are providing this version to give early visibility of the article. Please note that, during the production process, errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.

Global Adoption of Generative AI: What Matters Most?

Hassnian Ali*

haal50943@hbku.edu.qa

Hamad Bin Khalifa University, HBKU, Qatar

Atta ul Mustafa

attaulmustafa47@gmail.com

Hamad Bin Khalifa University, HBKU, Qatar

International Center for Research in Islamic Economics, ICRIE, Minhaj University Lahore, Pakistan

Ahmet Faruk Aysan
Hamad Bin Khalifa University, Qatar Foundation
Non-Resident Fellow Middle East Council on Global Affairs (ME Council)
Research Associate, the University College London
Centre for Blockchain Technologies (UCL CBT)
Hussnain756@gmail.com
ORCID: 0000-0001-7363-0116

*Corresponding Author: haal508943@hbku.edu.qa , Postal Address: Male Housing, Qatar Foundation, Doha, Qatar

Abstract
This study investigates the determinants of generative AI adoption across 136 countries, leveraging cross-sectional data from 2023 and employing a negative binomial regression model to address data overdispersion. Generative AI is a transformative technology that enhances operational efficiency, drives innovation, and creates economic value across sectors. Key findings reveal that IT infrastructure, R&D investments, and company investment in emerging technologies significantly foster generative AI adoption, while misaligned government policies may hinder it. The analysis identifies crucial determinants, including technological infrastructure, economic stability, regulatory environments, and workforce readiness, as pivotal to adoption rates. The study provides actionable insights for policymakers, industry leaders, and researchers, advocating for tailored policies, strategic investment in high-speed internet and cloud services, and refining government incentives to align with AI sector needs. This research uniquely contributes by offering a comprehensive, cross-country perspective on factors influencing generative AI adoption.

Keywords: Generative AI, future, Emerging Technologies, Global Adoption

1. Introduction

Generative Artificial Intelligence (AI) represents a transformative technology with the potential to significantly enhance operational efficiency, foster innovation, and create substantial economic value. By 2030, the global market for generative AI is projected to reach $110 billion, highlighting its growing significance across various sectors (McKinsey, 2023). However, the successful adoption of generative AI is not guaranteed, as it is influenced by a range of factors, including technological infrastructure, regulatory environments, organizational readiness, and the availability of skilled personnel. While existing literature has explored AI adoption in specific contexts such as healthcare and education (Elstad & Eriksen, 2024; Ivanov et al., 2024), there remains a significant gap in understanding how these factors interact on a global scale, particularly in the context of generative AI (Gupta & Rathore, 2024).

A crucial but often underappreciated determinant of generative AI adoption is the role of a positive organizational environment. Successful AI integration requires more than just advanced technology; it depends on the alignment between organizational culture, leadership, and the adoption of innovative tools (Dong et al., 2024). Without this alignment, organizations may face significant barriers, including inefficiencies, delays, or even project failures (Prasad Agrawal, 2024). This research emphasizes the importance of creating an environment conducive to AI adoption by addressing these internal and external challenges. Thus, beyond the technological infrastructure, the readiness of organizations and regulatory frameworks also plays a pivotal role in the diffusion of AI.

Despite the growing body of research on AI adoption, most studies have focused on specific sectors or technological subsets like Information and Communication Technology (ICT). These studies often overlook the broader implications of generative AI, a more recent and powerful subset of AI that is reshaping industries (Russo, 2024). Additionally, existing research tends to concentrate on individual countries or regions, leaving a substantial gap in understanding the global determinants of generative AI adoption. This paper seeks to address this gap by examining the factors that influence the adoption of generative AI across 136 countries, with particular attention to technological infrastructure, economic conditions, and organizational readiness.

Methodologically, this study employs a negative binomial regression model to analyze the impact of technological infrastructure and economic conditions on the preparedness of countries to adopt generative AI. This method is well-suited to handle the count-dependent variables in the dataset, which exhibit overdispersion, where the variance is greater than the mean (Lawless, 1987). The use of this advanced statistical technique ensures that the analysis captures the complexity of the global landscape of AI adoption.

Empirical findings reveal that robust IT infrastructure, R&D investments, and organizational readiness significantly enhance generative AI adoption, while misaligned government policies can hinder these efforts. Economic stability, as indicated by GDP per capita, further supports adoption, emphasizing the importance of favorable economic conditions. Negative correlations between certain policy factors and AI adoption suggest the need for a more strategic policy alignment to avoid creating inadvertent barriers to adoption.

This study makes two key contributions to the literature. First, it focuses specifically on generative AI, an emerging technology that has yet to be explored comprehensively at a global level. Second, it extends the analysis to multiple countries, providing a more nuanced

understanding of how generative AI adoption varies across diverse economic, regulatory, and technological environments. The findings offer valuable insights for policymakers, industry leaders, and researchers by identifying the key determinants of generative AI adoption and offering actionable recommendations for enhancing adoption in different geographic and regulatory contexts.

The remainder of the paper is structured as follows: Section 2 reviews the relevant literature on generative AI adoption, focusing on the technological, organizational, and environmental factors. Section 3 outlines the methodology, including the negative binomial regression model used to analyze adoption patterns. Section 4 presents the empirical results, and Section 5 discusses the implications for policymakers, organizations, and future research.

2. Literature Review

Generative AI has rapidly emerged as a transformative technology with applications across numerous sectors. Its adoption is shaped by various factors, including organizational readiness, infrastructure, perceived benefits, and ethical considerations. While there is extensive research on AI adoption, especially in education and the workplace, there remains a need for a deeper understanding of how these factors influence adoption globally and across different contexts.

In the educational sector, AI has proven to be a powerful tool for enhancing learning experiences and supporting educators. For instance, research by Ivanov et al. (2024) shows that factors such as perceived benefits, risks, and attitudes toward AI play a crucial role in determining the intention to adopt AI tools. Drawing on the Theory of Planned Behavior (TPB), their study found that attitude, subjective norms, and perceived control significantly affect the use of AI in educational institutions. Similarly, Elstad and Eriksen (2024) found that teacher self-efficacy and institutional support are key drivers of generative AI adoption in schools, particularly in contexts where AI is used for instructional support.

In the workplace, organizational factors are pivotal in determining AI adoption. Dong et al. (2024) examined how organizational listening, which enhances employees' perceptions of autonomy and competence, can foster a more positive attitude toward AI adoption. Their findings suggest that a supportive work environment can significantly influence employees' willingness to embrace AI tools, highlighting the importance of organizational readiness in successful AI integration.

While recognizing the potential of generative AI, the service industry faces several challenges in its adoption. Gupta and Rathore (2024) identified key barriers, including privacy concerns, regulatory challenges, and high costs. Their analysis underscores the complexity of AI integration in service settings, where trust, anticipation, and technological readiness are crucial factors. Overcoming these barriers requires advancements in technology and a concerted effort from organizations to engage stakeholders and address ethical and infrastructural concerns.

At the organizational level, studies like Prasad Agrawal's (2024) have highlighted the importance of infrastructure, regulatory frameworks, and organizational innovation in driving AI adoption. Using the Technology-Organization-Environment (TOE) framework, the research emphasizes the role of organizational readiness and institutional support in ensuring successful AI implementation. This is further supported by Rana et al. (2024), who examined how ethical considerations, such as fairness, transparency, and accountability, influence AI adoption in organizations. Their findings indicate that organizations that integrate ethical governance into

their AI strategies tend to perform better, reinforcing the importance of ethical considerations in the AI adoption process.

In terms of broader societal impacts, public institutions are also increasingly incorporating AI technologies to improve service delivery. Tomaževič et al. (2024) explored the adoption of AI in public institutions and identified key enablers such as employee readiness, cultural adaptability, and organizational structure. Their research shows that the successful integration of AI in public services depends on both technological capabilities and human factors. Similarly, studies like Kuberkar et al. (2024) examined the use of AI in smart city services, finding that while AI can improve citizen engagement and service efficiency, socioeconomic disparities often hinder equitable access to these technologies.

Despite the extensive research on AI adoption in specific industries and regions, there are still significant gaps in understanding the global determinants of AI adoption. Many studies, such as those by Ivanov et al. (2024) and Gupta and Rathore (2024), focus on sector-specific applications, leaving a gap in research addressing generative AI adoption globally. This study seeks to bridge this gap by exploring the technological, organizational, and regulatory factors influencing AI adoption across 136 countries, offering a more comprehensive view of how generative AI can be integrated into various contexts.

By examining individual and organizational AI adoption drivers, this study aims to contribute to the growing body of knowledge on generative AI and provide practical insights for policymakers, industry leaders, and researchers. Through a detailed analysis of the factors influencing AI adoption globally, the study offers a broader perspective on how generative AI can drive innovation while maintaining ethical governance and organizational efficiency.

3. Methodology

The study used five dependent and 13 independent variables. The study utilized data from 136 countries in the analysis of the year 2023. A list of countries is provided in Table 2 in the Appendix.

3.1. Rationale of variables, hypotheses and model

The selection of dependent and independent variables for this study is grounded in theoretical frameworks and empirical research that have previously explored the adoption of emerging technologies like generative AI. The dependent variable is drawn from *Electronics Hub*, which compiled data on over 90 generative AI tools across four categories: text, voice, audio, and image. The dataset provides a robust measure of generative AI adoption by analyzing monthly Google search volume for these tools in various countries. The search volume per 100,000 people serves as the dependent variable, offering insight into the level of interest and engagement with generative AI tools across countries.

The independent variables were selected to capture the economic, digital, and social dimensions that influence the adoption of generative AI. This selection is consistent with the literature on technology diffusion, and each variable is justified based on its relevance to generative AI. The rationale for choosing these variables is directly tied to the research questions and grounded in empirical studies, reflecting the complexity of generative AI adoption as discussed in the literature review. Higher GDP per capita growth is included as an independent variable because it reflects a country's economic capacity to invest in emerging technologies. As Waverman et al. (2005) pointed out, countries with stronger economic growth are better positioned to focus on technological advancements. The presence of a stable economy not only enhances the physical and human capital infrastructure but also fosters an

environment conducive to adopting cutting-edge technologies like generative AI. The unemployment rate offers insight into labor market dynamics. A lower unemployment rate may prompt firms to seek innovative technologies to compensate for labor shortages, while higher unemployment might indicate market conditions that deter firms from investing in automation and AI, as indicated by (Andoh-Baidoo et al., 2014). Private sector investment in emerging technologies is another critical factor. It directly reflects the willingness of firms to integrate generative AI tools into their business models, which is a significant driver of technology adoption. Bresnahan et al. (1995) emphasize the role of private sector R&D in accelerating the diffusion of new technologies, making it an essential variable in understanding generative AI adoption. Digital infrastructure plays a fundamental role in facilitating the use of generative AI. Both fixed broadband subscriptions and mobile cellular subscriptions serve as proxies for the robustness of a country's digital infrastructure, which is vital for the large-scale diffusion of digital technologies. This relationship is well-documented in studies by Czernich et al. (2011) and James (2010), who argue that digital infrastructure is a prerequisite for the successful adoption of AI technologies. Without adequate broadband and mobile connectivity, the integration of generative AI tools would be severely constrained, particularly in sectors that rely on real-time data processing and connectivity.

The ICT-skilled workforce variable captures the ability of a country's workforce to effectively use and adapt to new technologies. As Brynjolfsson et al. (2014) noted, countries with a highly skilled ICT workforce can derive greater productivity and innovation from adopting generative AI. This variable is crucial because generative AI requires technical infrastructure and a skilled labor force capable of effectively implementing and leveraging these tools. Governments also play a pivotal role in promoting the adoption of technologies. Government support for emerging technologies through policies like subsidies, tax reductions, and regulatory frameworks is crucial for overcoming financial and institutional barriers to adoption. Mazzucato (2013) argued that proactive government policies are essential in kickstarting the adoption of high-cost technologies like AI. This variable is significant in economies where private-sector investment alone may not be sufficient to drive widespread adoption. Including these variables allows for a comprehensive analysis of the various factors that facilitate or hinder the adoption of generative AI. To ensure clarity and relevance, the variables have been categorized into facilitating factors—those that are expected to positively impact generative AI adoption—and hindering factors, which could potentially limit or slow the diffusion of these technologies.

The dependent variable in this study is the search volume for generative AI tools across different categories, serving as a proxy for generative AI adoption in each country. The independent variables represent a combination of economic, social, and technological factors that either promote or inhibit the adoption of these tools. This categorization enhances the clarity of the model and provides a structured approach to understanding the factors that drive generative AI adoption.

The model for this study is designed to analyze the relationship between the independent variables and the dependent variable of generative AI adoption. The econometric model is as follows:

$$E(Z|X) = \alpha + \beta_1 FITI + \beta_2 CSS + \beta_3 RDSLT + \beta_4 CIET + \beta_5 ICT + \beta_6 MCS + \beta_7 GDPP \\ + \beta_8 FBS + \beta_9 GPI + \beta_{10} AET + \beta_{11} MCTS + \beta_{12} HWIA + \beta_{13} UNEM + \mu$$

Where:

- Z represents generative AI adoption across overall, text, image, voice, and video categories.

- X represents the independent variables.

- α is the intercept, and μ is the error term.

The hypotheses tested in this model are derived from the research questions and the theoretical foundations outlined in the literature review:

1. **H01**: Digital infrastructure does not contribute to the diffusion of generative AI.

2. **H02**: Private sector investment has no role in promoting the adoption of generative AI.

3. **H03**: Government policies play no role in the diffusion of generative AI.

4. **H04**: Economic conditions do not affect the adoption of generative AI.

The selection of variables reflects the complex interplay between economic, social, and technological factors in determining the level of generative AI adoption. Facilitating factors include digital infrastructure (FITI, FBS, MCS), private sector investment (CIET, RDSLT), ICT skills (ICT), and government support (GPI), all of which are expected to promote the adoption of generative AI. On the other hand, hindering factors, such as high unemployment (UNEM), may limit the capacity or willingness of firms and governments to invest in such technologies.

Table 1 encapsulates the list of the variables with their abbreviations and sources:

Table 1: List of variables with abbreviations

Category	Variables	Abbreviations	Sources
Dependent	Overall generative AI search volume per 100,000 people	Overall	Electronics Hub
	Text-related generative AI search volume per 100,000 people	Text	Electronics Hub
	Image-related generative AI search volume per 100,000 people	Image	Electronics Hub
	Voice-related generative AI search volume per 100,000 people	Voice	Electronics Hub
	Video-related generative AI search volume per 100,000 people	Video	Electronics Hub
Independent Variable	Foundational IT infrastructure	FITI	Oxfordinsights
	Computer software spending (% of GDP)	CSS	Oxfordinsights
	R&D Spending (log transformation)	RDSLT	Oxfordinsights
	Company investment in emerging technology	CIET	Oxfordinsights
	ICT skills	ICT	Oxfordinsights

	Mobile cellular subscriptions (per 100 people)	MCS	Oxfordinsights
	GDP per capita growth (annual %)	GDPP	World Development Indicator
	Fixed broadband subscriptions (per 100 people)	FBS	Oxfordinsights
	Government Promotion of Investment in Emerging Technologies	GPI	Oxfordinsights
	Adoption of Emerging Technologies	AET	Oxfordinsights
	Mobile-cellular telephone subscriptions	MCTS	Oxfordinsights
	Households with internet access	HWIA	Oxfordinsights
	Unemployment, total (% of total labor force)	UNEM	World Development Indicator

3.2. Regression Analysis Approach

In this study, we applied negative binomial regression to analyze the count data, which was characterized by overdispersion. Overdispersion occurs when the variance exceeds the mean, a common issue in count data, making it unsuitable for Poisson regression, which assumes equality between the mean and variance. The Poisson model underestimates standard errors under such conditions, leading to biased and unreliable results (Hilbe, 2011). Negative binomial regression, by contrast, incorporates an additional dispersion parameter that accounts for this overdispersion, providing more accurate and reliable estimates.

The decision to use negative binomial regression over Poisson regression is grounded in its ability to handle the variance structure of overdispersed data. Gardner et al. (1995) emphasized the value of this approach for count data that deviate from the Poisson assumption, particularly when skewness or outliers are present. The inclusion of an extra parameter to manage dispersion enables negative binomial regression to fit a broader range of count data, reducing bias in the estimates. Additionally, O'Hara and Kotze (2010) caution against using log transformations on count data for linear regression, as such transformations can introduce bias and distort results. Instead, they recommend regression models like the negative binomial, which are naturally suited to the distributional properties of count data.

The flexibility of the negative binomial model allows it to provide a more accurate fit for count data in a variety of contexts, making it the optimal choice for this study. In contrast to other models, such as linear regression with log-transformed data or the basic Poisson model, negative binomial regression offers more reliable and interpretable results by correcting for overdispersion. This correction ensures that the relationship between the independent and dependent variables is properly estimated, leading to valid conclusions.

Before applying the negative binomial regression, we conducted descriptive statistics to understand the data's distribution better and assess whether overdispersion was present. The analysis of the mean and variance of the dependent variables confirmed that the variance significantly exceeded the mean, justifying negative binomial regression for the final analysis. This approach ensures that the model fits the data correctly, addressing both overdispersion and the potential for skewness or outliers and providing high-quality, interpretable results.

4. Results

4.1. Descriptive statistics

Table 2 presents the descriptive statistics of the variables under consideration. The descriptive statistics provide a detailed overview of the variations across the variables related to generative AI adoption, reflecting both the range of adoption and the underlying infrastructural and economic factors influencing it. The overall adoption of generative AI, with a mean of 466.41 and a significant standard deviation of 679.22, highlights substantial variation among countries, as illustrated by the minimum and maximum values ranging from 1 to 5288. This wide disparity is also reflected in the percentiles, with the 25th percentile at 52.75 and the 75th percentile at 626.25, indicating that most countries fall between lower and middle adoption levels. At the same time, a few outliers demonstrate exceptional adoption rates. Among the generative AI categories, 'Text' tools exhibit the highest mean of 369.88 and a similarly wide range of adoption (standard deviation of 624.18), suggesting that text-based AI tools have seen broader global diffusion compared to other categories such as 'Image,' 'Voice,' and 'Video,' which display lower mean adoption rates of 75.07, 9.28, and 11.90, respectively. These lower categories are characterized by smaller interquartile ranges, indicating more consistent but generally lower adoption levels across countries. The foundational IT infrastructure (FITI) variable, with a mean of 65.06 and a relatively modest standard deviation of 20.60, reflects a fairly stable level of infrastructure support across countries essential for facilitating generative AI adoption. ICT skills, with a mean of 35.32, and households with internet access (HWIA) at 66.25 underscore the importance of digital literacy and access to technology in driving the diffusion of AI tools. The variation in R&D spending (RDSLT), with a mean of 26.85 and a maximum value of 108.59, points to significant disparities in national investments in research and development, which is a critical determinant of technological advancement and adoption. Economic indicators such as GDP per capita growth (GDPP), with a mean of 2.88 and standard deviation of 3.45, reveal considerable economic diversity among countries, further influencing their capacity to integrate advanced technologies like generative AI. The unemployment rate (UNEM), averaging at 8.95 but ranging from 0.1 to 27.83, highlights the role of labor market conditions in shaping the adoption landscape, as countries with lower unemployment may face pressures to invest in technologies that optimize labor productivity. Taken together, these descriptive results emphasize the interplay between digital infrastructure, economic conditions, R&D efforts, and government policy in shaping the adoption of generative AI technologies, with countries exhibiting stronger infrastructures, greater R&D investments, and proactive policies being better positioned to adopt and benefit from such innovations. Given the count nature of the dependent variable—reflecting the number of searches per country—and the presence of overdispersion in the data, the negative binomial regression model is an appropriate choice for analyzing the determinants of generative AI adoption. This model accounts for the overdispersion and offers a robust framework for understanding the variability in AI adoption across countries.

Table 2: Descriptive statistics

| Variable	Mean	Standard Deviation	Min	Max	25th Percentile	Median	75th Percentile
Overall	466.41	679.22	1	5288	52.75	215.5	626.25
Text	369.88	624.18	1	5236	32	119.5	461

Image	75.07	88.33	0	311	3.75	36	114.25
Voice	9.28	23.23	0	230	1	3	8
Video	11.90	11.20	0	57	2	9.5	17.25
FITI	65.06	20.60	15.6	99	49.05	70.15	81.5
CSS	21.82	20.46	0	98.23	5.27	16.045	31.80
RDSLT	26.85	23.19	0	108.59	11.49	22.13	36.15
CIET	32.12	23.96	0	100	18.75	28.125	42.1875
ICT	35.32	19.59	4.54	84.60	23.18	33.52	45.435
AET	37.32	16.79	8.75	77.15	27.42	38.085	47.09
MCTS	97.01	17.45	49.54	172.73	87.5	100	107.75
HWIA	66.25	31.42	5.53	100	42.09	72.50	92.675
UNEM	8.95	5.94	0.1	27.83	4.75	7.905	11.88
GDPP	2.88	3.45	-17.13	13.03	1.32	2.65	4.71
FBS	15.89	15.77	0	49.55	0.58	10.78	29.38
GPI	38.40	21.07	0	99.63	23.80	37.07	50.29

4.2. Correlation matrix and Multicollinearity test results

Figure 1 presents the correlation matrix of independent variables, highlighting key relationships among factors influencing generative AI adoption. Each cell in the matrix represents the correlation coefficient between two variables, with the color intensity reflecting the strength and direction of these correlations. A coefficient closer to 1 indicates a strong positive correlation, while values closer to -1 indicate a negative correlation. The diagonal line in the matrix, where each variable is correlated with itself, naturally shows a perfect correlation of 1.0. Strong positive correlations are evident between R&D Spending (RDSLT) and Company Investment in Emerging Technology (CIET) (0.72), and between Adoption of Emerging Technologies (AET) and both CIET (0.87) and Fixed Broadband Subscriptions (FBS) (0.74), underscoring the importance of infrastructure and corporate investment in fostering AI adoption. ICT skills also strongly correlate with AET (0.74), emphasizing the role of a skilled workforce. In contrast, Unemployment (UNEM) demonstrates negative correlations with most variables, indicating its hindering effect on AI diffusion. The relatively weaker correlations of GDP per Capita Growth (GDPP) with other factors suggest that while economic growth contributes, it may not be the primary driver of generative AI adoption. Overall, the matrix underscores the critical roles of infrastructure, corporate investment, and human capital in advancing generative AI adoption.

Figure 1: Correlation table

Correlation Matrix of Independent Variables
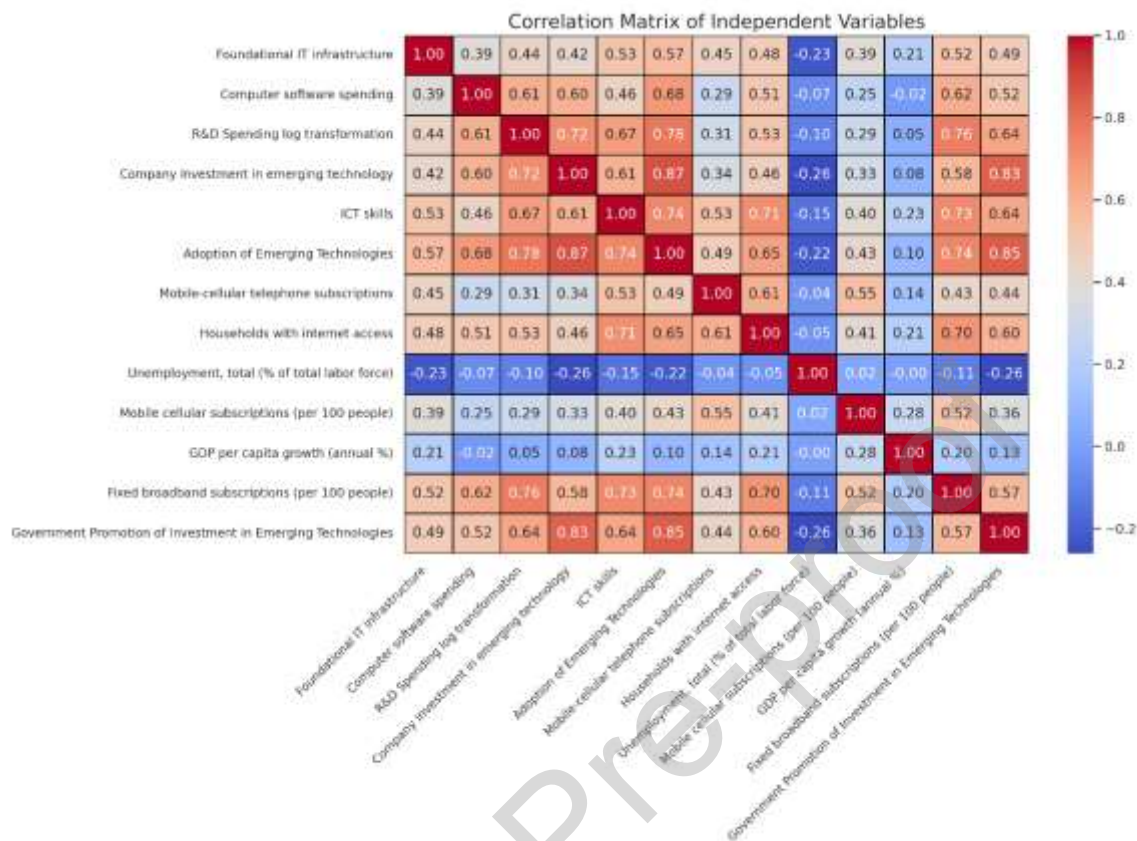
The Variance Inflation Factor (VIF) analysis results, presented in Table 3, show that all independent variables have VIF values below the threshold of 3, indicating no significant multicollinearity issues in the model. The variables with the highest VIF values are AET (2.91), CIET (2.89), and GPI (2.73), suggesting that these variables have relatively more robust collinearity with other predictors, though still within an acceptable range. GDPP (1.18) and UNEM (1.17) have the lowest VIF values, implying minimal multicollinearity influence. The mean VIF of 2.2 confirms that the overall multicollinearity level is well-controlled, supporting the robustness of the regression model.

Table 3: Result of Negative Binomial Regression

Variable	VIF	1/VIF
AET	2.91	0.34
CIET	2.89	0.35
GPI	2.73	0.37
FBS	2.65	0.38
RDSLT	2.5	0.4
ICT	2.33	0.43
HWIA	2.23	0.45
CSS	2.25	0.44
MCS	1.81	0.55

FITI	1.74	0.57
GDPP	1.18	0.85
UNEM	1.17	0.86
Mean VIF	2.2	

4.3. Main Regression Results and Discussion

The Negative Binomial Regression results in Table 4 provide valuable insights into the determinants of generative AI adoption across various categories (Overall, Text, Voice, Images, and Video). The coefficient for FITI is positive and significant across all categories, with values such as 0.013** for overall adoption and 0.028** for images, indicating that foundational IT infrastructure strongly supports the adoption of generative AI. Conversely, GPI shows a negative and significant relationship in all categories, with coefficients like -0.020** for overall and -0.065** for images, suggesting that government promotion of emerging technologies may not always be effective in encouraging generative AI adoption, possibly due to inefficiencies in implementation.

For economic factors, GDPG displays a significant positive impact on overall (0.055**) and text-based (0.071**) adoption, while it has no significant effect on voice or image adoption. CIET is also a strong positive driver in the overall (0.031**) and text (0.036**) categories, indicating that private sector investments play a crucial role in generative AI adoption. However, its influence diminishes for voice, images, and video, where coefficients are either negative or insignificant. AET positively impacts all categories, with coefficients like 0.028** for overall and 0.063** for images, highlighting the broad role of adopting emerging technologies in fostering generative AI diffusion.

Additional variables like MCTS (0.016**) and HWIA (0.023**) also show a positive and significant impact on overall adoption, reinforcing the importance of mobile subscriptions and household internet access in supporting generative AI. However, MCS presents a negative and significant coefficient for voice (-0.004**), indicating that mobile cellular subscriptions alone may not enhance voice-based AI adoption. Finally, UNEM shows a positive association with overall (0.055**) and text-based (0.065**) adoption, suggesting that higher unemployment may drive technological adoption as firms seek cost-cutting innovations.

In the discussion, the results highlight that FITI, AET, and HWIA are critical enablers of generative AI adoption, underscoring the importance of robust digital infrastructure. However, the negative impact of GPI suggests that government-driven policies may require more targeted approaches to be effective. Moreover, the positive impact of UNEM on adoption reflects how challenging labor markets might push firms to adopt AI technologies as a means to increase efficiency. Meanwhile, the mixed influence of RDSLT and FBS points to the complexity of translating digital investments into tangible AI adoption, indicating that other supporting factors may be necessary to fully harness the potential of these investments. . These results are consistent with (Waverman et al., 2005). Furthermore, the impact of technological variables generally are positive as well and is consistent with (Andoh-Baidoo et al., 2014; Baliamoune-Lutz, 2003; Sudan et al., 2010).

Table 3: Result of Negative Binomial Regression

	Overall	Text	Voice	Images	Video
main					
FITI	0.013**	0.011*	0.012**	0.028**	0.007*
	(0.005)	(0.006)	(0.004)	(0.008)	(0.004)

GPI	-0.020**	-0.016*	-0.021**	-0.065**	-0.013**
	(0.008)	(0.009)	(0.006)	(0.012)	(0.006)
CSS	-0.000	0.001	-0.003	0.002	0.002
	(0.005)	(0.006)	(0.004)	(0.009)	(0.004)
GDPG	0.055**	0.071**	-0.005	0.014	0.025
	(0.023)	(0.027)	(0.017)	(0.043)	(0.019)
CIET	0.031**	0.036**	-0.006	-0.005	-0.003
	(0.008)	(0.009)	(0.007)	(0.013)	(0.007)
ICT	-0.008	-0.008	0.001	0.004	0.003
	(0.005)	(0.006)	(0.004)	(0.008)	(0.004)
AET	0.028**	0.026**	0.034**	0.063**	0.029**
	(0.010)	(0.012)	(0.008)	(0.014)	(0.008)
MCTS	0.016**	0.014*	0.022**	0.010	0.006
	(0.006)	(0.007)	(0.005)	(0.009)	(0.005)
HWIA	0.023**	0.023**	0.029**	0.014*	0.018**
	(0.005)	(0.006)	(0.004)	(0.008)	(0.004)
MCS	-0.001	-0.000	-0.004**	-0.002	-0.000
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
FBS	0.004	0.000	0.025**	0.040**	-0.000
	(0.010)	(0.012)	(0.008)	(0.015)	(0.008)
UNEM	0.055**	0.065**	0.020	-0.003	0.025*
	(0.018)	(0.021)	(0.015)	(0.028)	(0.014)
RDSLT	-0.013*	-0.015*	0.005	-0.034**	-0.004
	(0.007)	(0.008)	(0.005)	(0.010)	(0.005)
Constant	-0.002	-0.275	-1.978**	-2.080**	-1.077**
	(0.482)	(0.556)	(0.448)	(0.801)	(0.443)
lnalpha					
Constant	-0.330**	-0.046	-0.995**	0.092	-1.236**
	(0.113)	(0.110)	(0.150)	(0.151)	(0.182)
Observations	136	136	136	136	136

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$

5. Conclusion and Implications

This study investigates the determinants influencing the adoption of generative AI across 136 countries, using a negative binomial regression model to examine the effects of technological infrastructure, economic conditions, and regulatory frameworks. The primary goal is to identify global factors that facilitate or impede the adoption of this transformative technology, which plays a crucial role in enhancing operational efficiency, driving innovation, and creating economic value across various sectors. Key factors such as robust technological infrastructure, economic stability, company investment in emerging technologies, organizational readiness, and a skilled workforce emerge as pivotal for AI adoption.

Empirical findings reveal that countries with developed IT infrastructure and higher research and development (R&D) investments are significantly more likely to adopt generative AI technologies. These elements provide a critical foundation for deploying advanced AI systems requiring significant computational resources and sophisticated data management. Economic stability, as indicated by GDP per capita growth, also positively impacts AI adoption, highlighting the importance of a strong economic environment. Company investment in new technologies further emerges as a crucial factor, emphasizing the role of innovation and readiness within organizations in embracing AI solutions.

However, the study also finds that government policies promoting investment in emerging technologies can have unintended negative effects if they are misaligned with the needs of the AI sector. The observed negative correlation suggests that poorly designed or overly rigid policies may create barriers rather than facilitate the adoption of generative AI. This finding underscores the need for more nuanced and tailored policy frameworks that address the specific needs of the AI industry to support widespread technological integration.

The implications of these findings are significant for both policymakers and industry leaders. For policymakers, the results highlight the need to develop targeted policies that enhance the technological infrastructure essential for AI deployment. Investments in high-speed internet, cloud services, and advanced computing resources are fundamental to creating an environment conducive to AI adoption. Additionally, regulatory frameworks must be aligned with the evolving needs of the AI sector to encourage innovation and reduce barriers to technological integration.

Several recommendations arise from this study. Policymakers should prioritize investments in high-speed internet and computing resources, essential for the successful implementation of generative AI technologies. Financial support for R&D, through grants, loans, or tax incentives, can stimulate company investments in emerging technologies, fostering a culture of innovation within organizations. Refining existing government policies to align with the specific demands of the AI sector will help remove barriers to adoption and drive global competitiveness. Moreover, organizations must invest in upskilling their workforce to fully leverage the benefits of generative AI, resulting in improved operational efficiency, innovation, and a competitive edge.

While this study provides valuable insights, it is not without limitations. First, the cross-sectional nature of the data limits the ability to capture the dynamic evolution of AI adoption over time. Future research could benefit from longitudinal studies to observe these trends. Second, this study focuses on macroeconomic indicators but does not delve into micro-level organizational factors, such as internal management practices or firm-level innovation culture. Future research should explore these micro-level dynamics to offer a more granular understanding of AI adoption. Lastly, this study predominantly focuses on technological and economic factors; future research could incorporate the role of social, ethical, and cultural

dimensions in shaping AI adoption. Addressing these limitations will provide a more comprehensive understanding of the factors driving generative AI adoption across different contexts.

References

Andoh-Baidoo, F. K., Osatuyi, B., & Kunene, K. N. (2014). ICT Capacity as the Investment and Use of ICT: Exploring its Antecedents in Africa. *Information Technology for Development*, *20*(1), 44–59. https://doi.org/10.1080/02681102.2013.804399

Baliamoune-Lutz, M. (2003). An analysis of the determinants and effects of ICT diffusion in developing countries. *Information Technology for Development*, *10*(3), 151–169.

Bresnahan Manuel, T. and T. (1995). General Purpose Technologies: 'Engines of Growth'? *Journal of Econometrics*, *65*(1), 83–108.

Brynjolfsson Andrew, E. and M. (2014). *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. W.W. Norton & Company.

Czernich, N., Falck, O., Kretschmer, T., & Woessmann, L. (2011). Broadband Infrastructure and Economic Growth. *Economic Journal*, *121*(552), 505–532. https://doi.org/10.1111/j.1468-0297.2011.02420.x

Dong, E., Liu, H., Li, J.-Y., & Lee, Y. (2024). Motivating employee voicing behavior in optimizing workplace generative ai adoption: The role of organizational listening. *Public Relations Review*, *50*(5). https://doi.org/10.1016/j.pubrev.2024.102509

Elstad, E., & Eriksen, H. (2024). High School Teachers' Adoption of Generative AI: Antecedents of Instructional AI Utility in the Early Stages of School-Specific Chatbot Implementation. *Nordic Journal of Comparative and International Education*, *8*(1). https://doi.org/10.7577/njcie.5736

Gardner, W., Mulvey, E. P., & Shaw, E. C. (1995). Regression Analyses of Counts and Rates: Poisson, Overdispersed Poisson, and Negative Binomial Models. *Psychological Bulletin*, *118*(3), 392–404. https://doi.org/10.1037/0033-2909.118.3.392

Gupta, R., & Rathore, B. (2024). Exploring the generative AI adoption in service industry: A mixed-method analysis. *Journal of Retailing and Consumer Services*, *81*. https://doi.org/10.1016/j.jretconser.2024.103997

Hilbe. (2011). Overdispersion. In J. M. Hilbe (Ed.), *Cambridge University Press* (2nd ed., pp. 141–184). Cambridge University Press. https://doi.org/DOI: 10.1017/CBO9780511973420.008

Ivanov, S., Soliman, M., Tuomi, A., Alkathiri, N. A., & Al-Alawi, A. N. (2024). Drivers of generative AI adoption in higher education through the lens of the Theory of Planned Behaviour. *Technology in Society*, *77*. https://doi.org/10.1016/j.techsoc.2024.102521

James, J. (2010). *Information Technology and Development: A New Paradigm for Delivering the Internet to Rural Areas in Developing Countries*. Routledge.

Kuberkar, S., Singh, S., & Singhal, T. K. (2024). Adoption intention of artificial intelligence enabled smart city services from citizens' perspective. *International Journal of Human Capital in Urban Management*, *9*(1), 29–46. https://doi.org/10.22034/IJHCUM.2024.01.03

Lawless, J. F. (1987). Negative binomial and mixed Poisson regression. *Canadian Journal of Statistics*, *15*(3), 209–225. https://doi.org/10.2307/3314912

Mazzucato, M. (2013). *The Entrepreneurial State: Debunking Public vs. Private Sector Myths*. Anthem Press.

McKinsey. (2023). *The State of AI in 2023: Generative AI's Breakout Year*.

O'Hara, R. B., & Kotze, D. J. (2010). Do not log-transform count data. *Methods in Ecology and Evolution*, *1*(2), 118–122. https://doi.org/10.1111/j.2041-210X.2010.00021.x

Prasad Agrawal, K. (2024). Towards Adoption of Generative AI in Organizational Settings. *Journal of Computer Information Systems*, *64*(5), 636–651. https://doi.org/10.1080/08874417.2023.2240744

Rana, N. P., Pillai, R., Sivathanu, B., & Malik, N. (2024). Assessing the nexus of Generative AI adoption, ethical considerations and organizational performance. *Technovation*, *135*. https://doi.org/10.1016/j.technovation.2024.103064

Russo, D. (2024). Navigating the Complexity of Generative AI Adoption in Software Engineering. *ACM Transactions on Software Engineering and Methodology*, *33*(5). https://doi.org/10.1145/3652154

Sudan, R., Ayers, S., Dongier, P., Muente-Kunigami, A., & Qiang, C. Z.-W. (2010). *The global opportunity in IT-based services: assessing and enhancing country competitiveness*. World Bank Publications.

Tomaževič, N., Murko, E., & Aristovnik, A. (2024). Organisational Enablers of Artificial Intelligence Adoption in Public Institutions: A Systematic Literature Review. *Central European Public Administration Review*, *22*(1), 109–138. https://doi.org/10.17573/cepar.2024.1.05

Waverman, L., Meschi, M., & Fuss, M. (2005). The impact of telecoms on economic growth in developing countries. *The Vodafone Policy Paper Series*, *2*(03), 10–24.

Declaration Statement

Appendix

Table 4: List of Countries

List of the Countries			
Albania	Dominican Republic	Lesotho	Rwanda
Algeria	Ecuador	Libya	Saudi Arabia
Angola	Egypt	Lithuania	Senegal
Argentina	El Salvador	Madagascar	Serbia
Armenia	Estonia	Malawi	Sierra Leone
Australia	Ethiopia	Malaysia	Singapore
Austria	Finland	Mali	Slovakia
Azerbaijan	France	Mauritius	Slovenia
Bahrain	Gabon	Mexico	Somalia
Bangladesh	Gambia	Mongolia	South Africa
Belarus	Georgia	Morocco	South Korea
Belgium	Germany	Mozambique	Spain
Benin	Ghana	Myanmar	Sri Lanka
Bolivia	Greece	Namibia	Sweden
Bosnia and Herzegovina	Guatemala	Nepal	Switzerland
Botswana	Haiti	Netherlands	Tajikistan
Brazil	Honduras	New Zealand	Tanzania
Bulgaria	Hungary	Nicaragua	Thailand
Burkina Faso	India	Niger	Togo
Burundi	Indonesia	Nigeria	Trinidad and Tobago
Cambodia	Iraq	North Macedonia	Tunisia
Cameroon	Ireland	Norway	Turkey
Canada	Israel	Oman	Turkmenistan
Chad	Italy	Pakistan	Uganda
Chile	Jamaica	Panama	Ukraine
Colombia	Japan	Papua New Guinea	United Arab Emirates
Congo	Jordan	Paraguay	United Kingdom
Costa Rica	Kazakhstan	Peru	United States
Cote d'Ivoire	Kenya	Philippines	Uruguay
Croatia	Kuwait	Poland	Uzbekistan
Cyprus	Kyrgyzstan	Portugal	Venezuela
Czech Republic	Laos	Qatar	Vietnam
DR Congo	Latvia	Romania	Zambia
Denmark	Lebanon	Russia	Zimbabwe

Histograms

Distribution of Overall

Distribution of Text

Distribution of Video

Distribution of Image

Distribution of Foundational IT infrastructure

Distribution of Voice

Distribution of Computer software spending

Distribution of R&D Spending log transformation

Distribution of Mobile-cellular telephone subscriptions

Distribution of Company investment in emerging technology

Distribution of Households with internet access

Distribution of ICT skills

Distribution of Unemployment, total (% of total labor force)

Distribution of Adoption of Emerging Technologies

Distribution of Mobile cellular subscriptions (per 100 people)

Distribution of GDP per capita growth (annual %)

Distribution of Fixed broadband subscriptions (per 100 people)

Distribution of Government Promotion of Investment in Emerging Te...