Logistic Regression and Predictive Analysis For AI Strategies in Public Services

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***Abstract* –The integration of digital capabilities and IT skills with government services in the public sector is crucial for societal and economic growth. The adoption of digital capabilities and technological advancements renders more efficacy and efficiency to the delivery of public sector services. However, governments face challenges in meeting the increasing demands from corporations and residents. To leverage emerging digital technologies, governments need to collaborate with residents, society, and enterprises while ensuring proper technological implementation. Every nation must structure itself and ensure that Artificial Intelligence (AI) and other emerging technologies are strategically incorporated to enhance the delivery of services to citizens. This study has used logistic regression analysis to explore the influence of factors such as digital capabilities, technology skills, innovation, and data capabilities on the implementation of AI-enabled public services. The Governments' Artificial Intelligence Readiness Index score of 100 countries, provided by Oxford Insights and IDRC, is used to analyze the impact. The findings reveal that the utilization of AI in public services significantly affects a nation's procurement of advanced technology, data capabilities, and innovative capacities.**

***Keywords* –data capabilities, innovation, Artificial intelligence, public services.**

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1. Introduction

The rapid pace of technological advancements in the twenty-first century has brought forth the advent of the Fourth Industrial Revolution (4IR), characterized by transformative technologies such as machine learning, automation, Internet of Things (IoT), big data analytics, and predictive analytics. These technologies have permeated various sectors and industries, including business, manufacturing, healthcare, education, agriculture, and more. This era of technological revolution presents both opportunities and challenges for societies and economies worldwide [1], [2]. Public sector services are no exception to the widespread infiltration of computers and machine intelligence systems into virtually every aspect of our lives.

In the era of rapid technological transformation, countries around the world are recognizing the need to integrate IT skills with government services in the public sector [3]. This integration is vital for improving public sector services in areas such as healthcare, education, agriculture, smart manufacturing, telecom and banking, traffic control, and public surveillance systems [4]. The key innovation lies in the adoption of Artificial Intelligence (AI) and other emerging technologies to enhance the delivery of public services to citizens. It is evident that businesses, enterprises, and nations, regardless of their size, must embrace these technological advancements to stay competitive in the ever-changing landscape [5], [6].

The utilization of AI and other Fourth Industrial Revolution (4IR) technologies is increasingly becoming a hallmark of leading industry players. From small firms seeking to enhance operations through predictive analysis to countries aiming to strengthen their defense capabilities with autonomous weaponry, the overarching objective of AI is to outperform the competition. The widespread adoption of 4IR technologies by enterprises clearly positions them as industry leaders. Consequently, the development and application of AI are poised to shape the geopolitical landscape, determining the influence that nations wield on the global stage [7].

In this context, this study aims to explore the impact of various factors such as digital capabilities, technology skills, innovation, and data capabilities on the implementation of AI-enabled public services. The study will delve into the strategies adopted by countries in integrating AI into their public sector services and analyze the potential benefits and challenges associated with AI implementation on a national level.

Majority of present-day AI applications focus on automating processes to enhance quality and productivity of operations. Companies manufacturing tangible goods make use of AI in various aspects of business operations, from product development, to sales and marketing, to customer support [8], [9]. AI-based product development helps in enriching and speeding up innovation resulting in new and progressive products. High precision manufacturing processes aid in production of high-quality equipment. Cutting-edge industrial processes like additive manufacturing increase overall productivity, product quality and operational efficiency [5]. Demand forecasting to reduce inventory costs, predictive maintenance to spot equipment malfunctions to prevent unplanned breakdowns, consumer behaviour prediction, causality determination, IT management, cyber security, are some of the areas where AI is put to efficient and beneficial use in the services industry. However, efficient application of AI, technological advancements, and business model changes are all connected with the government's effective use of AI [10], [11].

Recent times have seen a rapid increase in the application of AI technology in public services. It is now widely used for internal process in optimization of various services as well as for inspection, enforcement, and detection by enforcement authorities [12]. Personalized services, maintenance, forecasting, and policy-making fall within the middle category of AI application. However, knowledge collection and the facilitation of democratic processes are the two least used applications of AI in public services. These services mostly make use of robotics, speech/text recognition, and picture recognition [13]. On the other hand, "stand-alone" machine learning methods are quite frequently used. The development and delivery of AI solutions for public services are heavily dependent on the private sector, according to other studies on AI for public services. A majority of government organizations may not develop their own AI solutions, while some do. This dependency extends beyond the front-end services to the entire infrastructure for AI-based public services [2], [14].

During the 1980s AI had fallen short of meeting expectations and most of the ambitious goals were not met. Years had been spent in an attempt to accurately define human intellect, yet, the advances gained failed to live up to the initial excitement. However, despite all setbacks, AI still thrived, and late 1990s witnessed many landmark goals being achieved. Massive technological developments, machine learning, big data, reinforcement learning and deep learning algorithms based on neural networks have rendered more accuracy and precision to AI based applications [4], [15]. Other factors like silicon-level innovation, including the use of graphics processing units and tensor processing units, also played a role in the success of AI. Computers having exponentially higher computing capabilities are available to train on larger datasets using more sophisticated models. Hyperscale clusters are formed to combine this capability, which is then progressively made available to customers through the cloud [16], [17]. The massive volume of data being produced is now available to train AI systems. AI has made several breakthroughs as a consequence of system-level advancements. From text and sentiment analysis, face recognition, medical image diagnosis, smart appliances, recommender systems, personal assistants, to autonomous vehicles, we find machines handling highly sensitive tasks involving large amounts of data with great accuracy, efficiency and speed. This calls for integration of several fields like robotics, machine vision, sensors, mapping, LIDAR, navigation algorithms, and satellite technology [18], [19].

Although there have been significant advancements, there are still several challenging issues that require further scientific discoveries. The "narrow AI" field—where machine-learning approaches are being developed to address particular issues, such as those in natural language processing—has made the most headway thus far achieving artificial general intelligence is considered a significant milestone in the field of AI and is seen as a challenging endeavor. The goal is to create AI that can solve broad concerns in a manner similar to humans.

Artificial intelligence (AI) has the potential to transform the country by enhancing the lives of individuals, increasing productivity, and providing higher quality services. However, before taking the plunge, it is important to assess how ‘AI-ready’ are the nations to operate and avail AI based solutions. With the aim of measuring the readiness of the government to deploy AI, Oxford Insights created the Government Artificial Intelligence Readiness Index (AIRI) in 2017 [20]. This data generated AI readiness index scores for 194 nations based on how ready each one was to employ AI in public services. The present study undertakes AI readiness index scores of 100 top countries in Government digital public services, government procurement of advanced technology, data capability, technology skills, and the innovation capabilities. The study aims to explore various inputs by the government and its influence on the use of AI strategy for effective public services.

It was observed that the top twenty positions on the AI Readiness Index are predominantly occupied by governments of Western Europe, Canada, Australia, New Zealand, and four Asian nations, including India. These countries exhibit strong economies, vibrant cultures, and well-established governance systems, contributing to their high rankings. Notably, no country from Latin America or Africa managed to secure a place within the top twenty. Table 1 presents the ranked countries in the regions, along with their respective positions among the 194 countries considered.

Table 1 AI readiness index score and the Global rank

Region	Country	Score	Rank
Asia-Pacific	**Singapore**	**9.186**	**1**
	Japan	8.582	10
	India	7.515	17
	United Arab Emirates	7.445	19
	China	7.370	20
Australia /NZ	**Australia**	**8.126**	**11**
	New Zealand	7.876	13
North America	**United States of America**	**8.804**	**4**
	Canada	8.674	7
Western Europe	**United Kingdom**	**9.069**	**2**
	Germany	8.810	3
	Finland	8.772	5
	Sweden	8.674	6
	France	8.608	8
	Denmark	8.601	9
	Norway	8.079	12
	Netherlands	7.659	14
	Italy	7.533	15
	Austria	7.527	16
	Switzerland	7.461	18

Data Source: Oxford Insights and the IDRC [20]

2. Material and methods

The study collected data from Oxford Insights on AI readiness scores for the top 100 countries out of the total 194 global economies. To normalize the scores, they were divided by the maximum score and multiplied by 100, resulting in data ranging from 0 to 100. The analysis focused on the preparedness of each country's government across various input parameters, including digital public services, government procurement of technology, data capabilities, technology skills, and innovation capabilities, as well as the output parameter of AI utilization (as shown in Table 2). Logistic Regression (LR) analysis was employed to leverage the predictive capabilities of Artificial Intelligence.

The objective is to identify the key input variable impacting the government effectiveness in providing public services, as well as, to determine the causal links.

LR is a popular binary classification algorithm based on supervised learning. It predicts the probability of a dichotomous variable (DVs) based on a given set of independent variables (IDVs). In the study 'Use of AI' (1, success) and (0, failure) has been used as DV. The logistic regression model predicts P(Y=1) as a function of Xs (IDVs). The probability of outcome variable results in success or failure, thus characterizing as binary classification. Unlike linear regression models that provide a continuous output based on mean square error, logistic models utilize a sigmoid function to fit an 'S' shaped curve, resulting in a better fit for the data. The logistic regression model provides a discrete output based on maximum likelihood estimation [21].

The study includes scatter plots, correlation plots, descriptive statistics, and a correlation matrix of the variables. All statistical analyses were conducted using the R environment.

Table 2 Description of variables, sources, and type

Variable	**Description**	**Scale**	**DV/ IDV**	**Source**
AI	Use of AI	Binary (0, 1)	DV	WEF Global Competitiveness Report 2018
GDS	Technology skills	Continuous (0 - 100)	IDV	
GAT	Innovation capability	Continuous (0 - 100)	IDV	
GDC	Digital public services	Continuous (0 - 100)	IDV	UN government Survey
GTS	Government Procurement	Continuous (0 - 100)	IDV	WEF Networked Readiness Index 2016
GIC	Data Capability (in govt.)	Continuous (0 - 100)	IDV	UN e-government index 2018

*DV-*Dependent* IDV-*Independent variable*

3. Results

A. Descriptive Statistics

Table 3 displays the descriptive statistics for the Governments Index scores of the variables analyzed in the study. This table provides valuable information such as the average index scores and standard deviations for two categories based on the adoption of AI approaches (Yes/No). Furthermore, the table includes results from independent sample t-tests, indicating the significance levels to determine if there are any noteworthy variations in the index scores as a result of nations' adoption of AI techniques. These statistics offer a comprehensive overview of the data and help identify potential disparities in the index scores between the two groups.

Table 3 Results of statistical differences between the group

Variable	AI Strategy	Mean	SD	*t*-statistics	Sig-value
GDS	Yes	95.46	3.54	5.224	**0.000****
	No	74.02	14.68		
GAT	Yes	55.64	7.19	2.517	**0.013***
	No	48.96	9.13		
GDC	Yes	83.81	10.14	4.281	**0.000****
	No	66.97	13.61		
GTS	Yes	71.87	7.52	2.678	**0.009****
	No	60.56	14.9		
GIC	Yes	74.29	8.51	7.529	**0.000****
	No	43.14	14.5		

* Significant at 5% level ** Significant at 1% level

It is abundantly obvious that countries with established AI policies have higher index scores (mean score: 79.88) than nations without such plans (mean score: 53.24). It is demonstrated that countries with an AI assisted strategy have much greater levels of government effectiveness than those without one. The t-statistics value equals 4.830 with significance value less than 1 per cent confirms that the difference in the index scores is significant. The use of AI enabled strategy in digital public services, government acquisition of cutting-edge technology, data capability, technical skills, and innovation capabilities, revealed similar results and confirms that the difference is significant. These are determined to be inconsequential; the difference was found to be considerable across the board for all factors.

B. Correlation Analysis

In Figure 1, the heat map illustrates the correlation matrix, indicating the strength of the relationship between the variables. The observations reveal significant and positive correlations among all the variables: data capability, technology skills, digital public services, government procurement of advanced technology, and innovation capabilities.

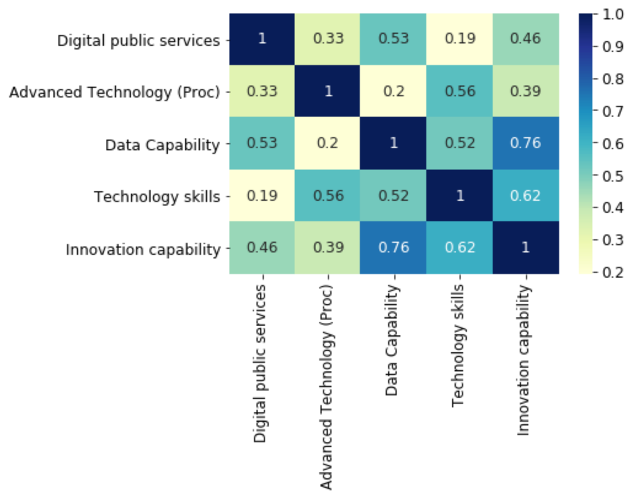

Figure 1 Correlation Matrix (heat map)

Figure 2 presents the pair-wise plots of the independent variables (IDVs) examined in the study. These plots provide a visual representation of the relationships between the input variables, namely data capability, technology skills, digital public services, government procurement of advanced technology, and innovation capabilities.

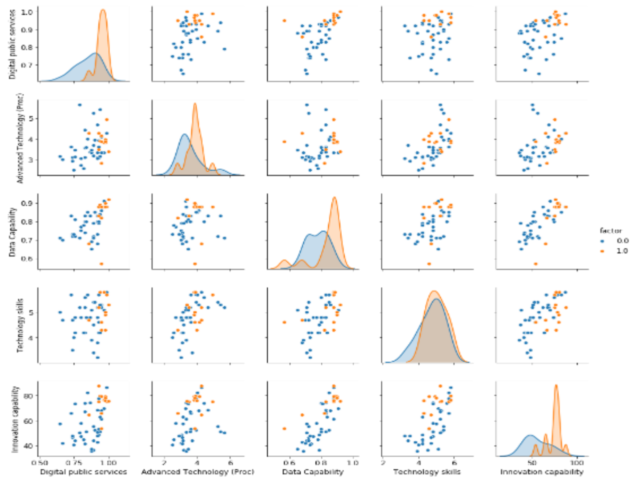

Figure 2 Pair-wise Scatter plot

C. Logistic regression analysis

The logistic regression results in Table 4 provide insights into the probability of utilizing AI strategies in the country. This analysis examines the impact of various factors, including data capability, technology skills, digital public services, government procurement of advanced technology, and innovation capabilities, on the likelihood of using AI strategies.

The results show significant positive impact of digital public services ($\beta = 0.420$, $e^{\beta}=1.522$ $p<0.01$), data capability ($\beta = 0.416$, $e^{\beta}=1.516$ $p<0.05$), technology skills ($\beta = 0.637$, $e^{\beta}=1.891$ $p<0.05$) and innovation capability ($\beta = 0.330$, $e^{\beta}=1.39$, $p<0.01$) on use of AI strategy. Government procurement of technology ($\beta =-1.250$, $e^{\beta}=0.287$, $p>0.05$) was found insignificant for effective use of AI strategy in the country.

The positive coefficients show that increased use of digital public services, data capabilities, technology skills, and innovation capabilities increases the use of AI strategies in the country for efficient and optimal delivery of public services.

The odds ratio (e^{β}) presents the association of IDVs on the probability outcome of AI (DV). The odds ratio of digital public services 1.522 indicates that the countries delivering digital public services have 52.2% (1.52-1 =0.52) more odds of using AI strategy for the public delivery in their countries. The countries having data capabilities, technology skills, and innovation capabilities have 51.6%, 89.1%, and 39% more odds of using AI strategy respectively. The model shows prediction accuracy of 73%.

Table 4 Results of logistic regression

IDVs	Coefficient ‘β’	St. Error	Z	P>|z|	LCL	UCL	Odds ratio e^{β}
Digital public services	0.420	0.147	2.857	**0.0043**	0.129	0.711	1.522
Government procurement	-1.250	1.250	-1.000	0.3173	-3.725	1.225	0.287
Data capability	0.416	0.193	2.155	**0.0311**	0.034	0.798	1.516
Technology skills	0.637	0.316	2.016	**0.0438**	0.011	1.263	1.891
Innovation capability	0.330	0.110	3.000	**0.0027**	0.112	0.548	1.391

4. Conclusion

Adoption and integration of emerging 4IR technologies has become imperative to stay in step with the technological expansion in the present times. Early adopters stand to gain an edge over the others by reaping the benefits of low operating costs, improved throughput and optimal performance. Every nation must be equipped to deal with the constant evolution of digital technology [22], [23]. This requires a data-centric strategy that is both more imaginative and collaborative. Every government strategy must be planned to have the appropriate architecture. More importantly, governments must evaluate their success in providing public services to citizens and incorporate modifications, wherever necessary, on a regular basis [24], [25].

The findings in the study bring to light gaps in the government’s AI implementation plans and urge policymakers to take appropriate actions to prevent growing global inequality. Government may benefit from the possibilities presented by new technology and enhance the perception of government operations by individuals. The results were obtained by applying logistic regression analysis. The outcomes emphasize the importance of digital public services, internal data capability, and innovation capability with regard to implementation of AI in the provision of public services. The results indicate that governments must invest in developing data capabilities and skills of their own personnel in pursuance of leading the country in the digital age with higher efficiency. It is argued that the negatives of technology adoption are displacement of labor, particularly in low skilled occupations, and the widening of the social inequality gap. In order to counteract this, government must also enhance its social and economic policies by providing skill enhancement and personnel training at affordable costs. Upskilling personnel is crucial to effective implementation and use of AI.

In addition to the general objectives and benefits of digital government strategies and programmes (such as effectiveness, cost and time savings, service improvement, improved accessibility and inclusion of services), AI in public services may also contribute in its own unique way to meet such objectives. The current study offers significant support for its claims based on the Index scores of each nation and demonstrates a strong propensity for applications in risk management, public safety and surveillance, and internal process optimization.

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