Determinants of Artificial Intelligence (AI) Readiness and Adoption in Public Sector Governance

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ABSTRACT

Artificial intelligence (AI) is increasingly recognized as a critical driver of digital transformation and improved public sector governance. Despite national initiatives such as the Philippine National Artificial Intelligence Strategy Roadmap, the adoption of AI within National Government Agencies (NGAs) and Local Government Units (LGUs) remains uneven and at an early stage. This study assesses the determinants of Artificial Intelligence (AI) readiness and adoption within the Philippine public sector, specifically focusing on National Government Agencies (NGAs) and Local Government Units (LGUs). Despite national initiatives like the National AI Strategy Roadmap, a gap persists between digital transformation goals and the actual capacity of public institutions to implement AI effectively. The research employed a quantitative descriptive-correlational design using a structured survey questionnaire. Data were gathered from 128 respondents, including government officials, ICT staff, and administrators in the Province of Bataan. The study utilized the Technology–Organization–Environment (TOE) Framework, Diffusion of Innovation (DOI) Theory, and Institutional Theory to analyze variables such as technological, human resource, and organizational readiness.

The findings reveal a satisfactory "Good" level of overall AI readiness (Composite Mean = 2.67), with technological readiness ranking highest. However, the level of AI adoption was rated as "Fair" (Composite Mean = 2.43), indicating that while foundational elements exist, they are not yet robust enough for extensive implementation. A significant digital divide was identified: NGAs (Mean = 2.75) scored statistically higher than LGUs (Mean = 2.36) across all readiness dimensions. Financial and logistical support emerged as the most significant organizational barrier to adoption.

The study concludes that higher readiness levels directly correlate with more successful AI adoption. While policy frameworks are emerging, a critical "policy-implementation gap" exists due to inadequate technical infrastructure and a shortage of skilled personnel. Proposed strategic interventions include institutionalizing AI governance structures, mandating continuous upskilling programs rather than isolated seminars, and formalizing public-private partnerships to bridge internal capacity gaps.

Keywords: Artificial Intelligence, Public Sector Governance, AI Readiness, AI Adoption, NGAs, LGUs, Digital Transformation.

INTRODUCTION

While advanced nations like Singapore and the US are already using AI to streamline public services, many other countries are still trying to bridge the gap between policy and practice. In the Philippines, the government is eager to transform into a regional AI hub, guided by the DTI's 2021 National AI Strategy Roadmap (PIDS, 2021) and digital infrastructure projects led by the DICT (2024). However, moving from a plan to a reality is proving difficult. Many local and national agencies are currently "stuck in the starting blocks" because they lack the necessary technical equipment, funding, and—most importantly—skilled staff to manage these new technologies. To make AI work for the Filipino people, the focus needs to shift toward building better data systems and clear ethical rules. By addressing these practical hurdles today, the government can create a future where public service is more transparent, efficient, and genuinely focused on the community's needs (Public Service Digitalization in the Philippines, 2024).

Despite national digital transformation goals, a significant gap exists because Philippine government agencies lack the funding, skilled personnel, and clear policy frameworks necessary for effective AI integration. This study is essential to provide the localized evidence and measurement tools needed to help policymakers bridge these gaps and modernize public governance through a deeper understanding of technological, human, and organizational factors.

This research integrates the Technology–Organization–Environment (TOE) Framework (Tornatzky & Fleischer, 1990), Diffusion of Innovation (DOI) Theory (Rogers, 2003), and Institutional Theory (DiMaggio & Powell, 1983 as cited by Greenwood, R., & Meyer, R. E. (2008) to evaluate the technological, organizational, and environmental factors driving AI adoption in the Philippine public sector. By applying Tukman's Input-Process-Output (IPO) model, the study analyzed how these theoretical determinants serve as inputs that are processed through surveys and statistical tools to ultimately produce a strategic intervention for managing AI readiness across National Government Agencies and Local Government Units.

Alhosani and Alhashmi (2024) mentioned Revenue NSW (2018) when AI was utilized to identify in vulnerable populations—approximately 46,000 individuals—the agency has moved beyond traditional enforcement models that historically only recognized financial hardship after punitive action had commenced. This shift demonstrates that AI in the public sector can serve a dual purpose: increasing the efficiency of the garnishee process while simultaneously safeguarding vulnerable citizens from the compounding effects of unpayable debt.

Hwang (2025) illustrated in his paper on AI service cases in the public sector the types of applications available and their technological and societal repercussions. The study introduces newly announced public AX (AI Transformation) projects in Korea's Ministry of Science and ICT, together with the AI government strategies and goals of Korea's new administration, which focus on strategies for planning with a focus on value-free domain, risk management, and return on investment. In the study of Yigitcanlar, et al. (2024) over the past decade, local governments in the US, China, and the UK have led a significant surge in AI adoption, primarily utilizing Natural Language Processing and Robotic Process Automation to optimize 28 different service areas. The technology is most frequently applied to information management, administrative back-office tasks, and traffic systems to improve overall urban efficiency. By documenting these trends, the study provides a vital strategic framework for policymakers to align future AI integration with the evolving needs of their communities.

This study assesses the determinants of AI readiness and adoption within National Government Agencies (NGAs) and Local Government Units (LGUs) through a quantitative lens. It investigates how demographic profiles, organizational factors, and human resources influence the public sector's ability to integrate AI technologies. Ultimately, the research aims to identify significant relationships between readiness and adoption to propose strategic interventions for responsible AI governance.

METHODS

The study employed a descriptive-correlational research design to determine the relationship between the identified determinants—technological readiness, human resource readiness, organizational readiness, technological adoption, human capability and competence, organizational support, and policy environment—and the level of AI readiness and adoption in public sector governance. The descriptive aspect described the current conditions of AI integration among National Government Agencies (NGAs) and Local Government Units (LGUs), while the correlational approach measured the association between the determinants and AI adoption levels. The main data-gathering tool of this study was a structured survey questionnaire developed by the researcher based on the identified variables designed to measure the level of readiness and adoption of Artificial Intelligence (AI) in some public sector governance among National Government Agencies (NGAs) and Local Government Units (LGUs).

Descriptive statistics such as frequency, percentage, mean, and standard deviation were used to describe the respondents' demographic profile and to determine the overall level of technological readiness, human resource readiness, organizational readiness, technological adoption, human capability and competence, organizational support, and policy environment were employed in the study. For inferential analysis, the Pearson Product-Moment Correlation Coefficient (r) was used to determine the relationship between AI readiness and adoption, as well as among the identified determinants. The Mann Whitney U-Test, a non-parametric test was also used to determine significant difference at 0.05 level of significance. The null hypotheses was tested using the non-parametric test Kruskal Wallis H-Test to test significant difference at 0.05 level and 4 degrees of freedom. All statistical computations were processed using the Statistical Package for the Social Sciences (SPSS) software or equivalent analytical tools. A significance level of 0.05 was applied as the criterion for determining the statistical significance of the results.

RESULTS AND DISCUSSION

Data reveals that from the total of 128 respondents, 74 or 57.81% of the respondents are employed in the national government agencies (NGA), and 54 or 42.19% are employed in the local government unit (LGU). The data indicate a considerable implication concerning the centralization and dominance of National Government Agencies (NGAs) in the initial assessment of artificial intelligence readiness and its subsequent implementation.

A total of 80 individuals, representing 62.50% of the sample, are employed in technical positions, whereas 48 individuals, representing 37.50%, hold administrative roles. The higher representation of technical personnel offers a substantial insight into AI readiness. However, it may also introduce a significant degree of perspective bias. In contrast, the standpoint of administrators, representing 37.50% of the respondents, is crucial in understanding the organizational and governance facilitators associated with the adoption of artificial intelligence (AI). This perspective emerged as a significant emphasis pertaining to the public sector (Selten & Klievink, 2024).

As to the years of services in the public sector 57 or 44.52% have 1 to 5 years; 29 or 22.66% have 6 to 10 years; 21 or 16.41% have 11 to 15 years; while 13 or 10.16% have less than 5 years; and 8 or 6.25% have more than 5 years. The data indicate that the public sector workforce is primarily concentrated within the early to mid-career stages. The distribution exerts a reasonable influence on the readiness for and adoption of artificial intelligence within the public sector governance. The major service cohorts consist of individuals with service durations of 1 to 5 years (44. 53%), 6 to 10 years (22.66%), and 11 to 15 years (16.41%) representing 83 6% of the total respondents.

There were 59 or 46.09% have minimal involvement; 43 or 33.59% have moderate involvement; 59 or 46.09% have minimal involvement; 17 or 13.29% have high involvement; and 9 or 7.03% have no involvement in the digital transformation program. The situation in the public sector's preparedness could undeniably be perceived critical when a significant majority of respondents have minimal or moderate involvement in ICT or Digital Transformation programs. With a registered 79.68% of combined total respondents including the 7.03% with no involvement signifies a clear and substantial proof of readiness gap that may impede AI integration.

Table 1 shows that the Technological readiness Mean=2.68 and SD=0.75 indicate that the readiness is good. It is shown that in terms of technological readiness, the highest mean is found in indicator 2 with a Mean=2.76 and SD=0.74. The lowest is found in indicator 4 with a Mean=2.58 and SD=0.76, both indicating agreement among the respondents.

Table 1 Level of AI readiness among NGAs and LGUs in terms of Technological Readiness

Variables	AWM	SD	DI	Rank
1. Our agency/LGU has sufficient ICT infrastructure to support AI-related systems.	2.70	0.70	Agree	2
2. The internet connectivity and digital platforms in our organization are reliable for AI operations.	2.76	0.74	Agree	1

3. Our data management systems are capable of supporting AI tools and analytics.	2.68	0.76	Agree	3
4. We have adequate cybersecurity measures to protect data used in AI applications.	2.58	0.76	Agree	5
5. Our organization is already using or testing AI-enabled technologies in some areas of operation.	2.66	0.78	Agree	4
Average Weighted Mean	**2.68**	**0.75**	**Agree**	

Legend: 3.25-4.00 Strongly Agree (Excellent); 2.50-3.24 Agree (Good);1.75-2.49 Moderately Agree (Fair); 1.00-1.74 Strongly Disagree (Poor)

The findings show a technological readiness with composite mean score of 2.68 (Good), indicates that the public sector organization has a basic but not yet mature digital capacity for advanced initiatives like AI. The high rating on internet connectivity and digital platforms indicates that foundational ICT infrastructure is established for routine digital operations. The successful digital transformation efforts is not an assurance if the there is substantial degree of rating on infrastructure development. Neumann (2024) emphasized that many public sector organizations have "*surface-level readiness*" as there are initiatives that are focused on hardware and connectivity like e-government system and digital platforms. However, they are still weak on government mechanisms, institutional capacity as well as needed protections for responsible use of AI. The lower mean rating in cybersecurity (M=2.58) and in data management (M=2.68) clearly shows readiness gaps that have critical implication for safe and reliable use of advanced technology in public sector governance.

Table 2 Level of AI readiness among NGAs and LGUs in terms of Human Resource Readiness

Variables	AWM	SD	DI	Rank
1. Our personnel have basic knowledge and understanding of artificial intelligence concepts.	2.55	0.77	Agree	3
2. Employees are provided with training or capacity-building programs on AI or emerging technologies.	2.52	0.78	Agree	4
3. Staff members are open to using AI tools in their daily tasks and decision-making.	2.57	0.78	Agree	2
4. There are personnel in our organization who are capable of managing or developing AI systems.	2.51	0.79	Agree	5
5. Leadership actively supports and encourages employees to learn about and adopt AI technologies.	2.66	0.80	Agree	1
Average Weighted Mean	**2.56**	**0.78**	**Agree**	

Legend: 3.25-4.00 Strongly Agree (Excellent); 2.50-3.24 Agree (Good);1.75-2.49 Moderately Agree (Fair); 1.00-1.74 Strongly Disagree (Poor)

Table 2 reveals that the readiness of NGAs and LGUs in terms of Human Resource (Mean=2.56, SD=0.68) is good. The highest mean is found in indicator 5 (Mean=2.66, SD=0.80) and the lowest is found in indicator 4 (Mean=2.51, SD=0.79), both indicating agreement among the respondents. The composite mean of 2.56 signifies generally "good" level of AI adoption as far as NGAs and LGUs human resource readiness is

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concerned. This points that the public sector employees have baseline AI awareness, literacy and receptiveness that are exhibited in their routine work.

The notable high rating for "leadership support" with a registered Mean equal to 2.66 is in consonance with the assertion of Kankanhalli et.al. (2019) that to set clear direction in promoting culture of innovation and boost employee's morale to engage AI practices in workforce necessitates strong leadership support among senior officials. The registered low mean score for AI management and development (M-2.51) indicates lack of qualified personnel, a challenge that is felt not only in the country but likewise felt worldwide.

Table 3 Level of AI readiness among NGAs and LGUs in terms of Organizational Readiness

Variables	AWM	SD	DI	Rank
1. Our agency/LGU has policies or strategic plans that include AI adoption or digital transformation.	2.59	0.77	Agree	2
2. Management allocates budget and resources to support AI-related initiatives.	2.53	0.70	Agree	5
3. Our organization's leadership is committed to promoting AI-driven innovation.	2.54	0.73	Agree	4
4. There is a culture of openness to technological change within our organization.	2.56	0.78	Agree	3
5. Our agency/LGU collaborates with other institutions (government, private, or academic) to explore AI solutions.	2.60	0.76	Agree	1
Average Weighted Mean	**2.56**	**0.75**	**Agree**	

Legend: 3.25-4.00 Strongly Agree (Excellent); 2.50-3.24 Agree (Good);1.75-2.49 Moderately Agree (Fair); 1.00-1.74 Strongly Disagree (Poor)

Table 3 data shows that the readiness of NGAs and LGUs in terms of Organizational Readiness (Mean=2.56, SD=0.75) is good. The highest mean is found in indicator 5 (Mean=2.60, SD=0.76) and the lowest is found in indicator 2 (Mean=2.53, SD=0.70), both indicating agreement among the respondents.

The results of the organizational readiness assessment reveal that government agencies demonstrate a generally *"Good"* level of readiness for AI adoption, indicated by the composite mean of 2.56. This reflects a foundational alignment of strategic intent, leadership commitment, and openness to change—three dimensions consistently identified in the literature as core pillars of readiness frameworks.

Table 4 reveals that the overall readiness for artificial intelligence (AI) among National Government Agencies (NGAs) and Local Government Units (LGUs) is deemed satisfactory, as reflected by a mean score of 2.67 and a standard deviation of 0.74. This implies that these institutions have developed moderately strong foundations for the integration of artificial intelligence technologies. The dimension characterized by the highest rating, namely Technological Readiness (M = 2.68, SD = 0.75), signifies that agencies have commenced investments in digital infrastructure and information and communication technology (ICT) systems that support the effective implementation of artificial intelligence. On the other hand, both the Human Resource Readiness and Organizational Readiness registered a Mean = 2.56 classified as "good" implementation category. It is noteworthy that these variables are ranked lower than the technological factors.

Table 4 Summary of Level of Assessment of AI Readiness among NGAs and LGUs

Variables	AWM	SD	DI	Rank
Technological Readiness	2.68	0.75	Agree	1
Human Resource Readiness	2.56	0.78	Agree	2.5
Organizational Readiness	2.56	0.75	Agree	2.5
Composite Mean	**2.67**	**0.74**	**Agree**	

Legend: 3.25-4.00 Strongly Agree (Excellent); 2.50-3.24 Agree (Good);1.75-2.49 Moderately Agree (Fair); 1.00-1.74 Strongly Disagree (Poor)

Table 5 presents the result of the analysis using the Mann Whitney U-test, which is a non-parametric test, indicates that there is enough evidence to claim that there exists a significant difference in AI readiness in terms of agency classification (U=1496.50, p=0.013), human resource readiness (U=1582.50, p=0.041), organizational readiness (U=1582.50, p=0.021), and policy environment (U=1330.50, p=0.033), considering the agency classification of the respondents. It is further confirmed by the overall U-value of 1486.50, significant at 0.013 which is statistically lesser than the alpha of .05, thus, rejecting the null hypothesis. it can be gleaned that the rating provided by the NGA (Mean=2.75, Mean Rank=72.77) is statistically greater than the LGU (Mean=2.36, Mean Rank=52.14). The disparity in artificial intelligence readiness between national government agencies (NGAs) and local government units (LGUs) indicates the existence of a digital divide within the public sector. This phenomenon represents a prevalent challenge associated with the adoption of emerging technologies in governance, particularly within the context of developing nations.

Table 5 Significant Difference Between AI Readiness of NGAs and LGUs vis-à-vis Agency Classification

Variables	Group	Mean	Mean Rank	U	Sig.	Decision on H_o	Interpretation
Technological Readiness	NGA	2.79	71.28	1496.50	.013	Reject	Significant
	LGU	2.51	55.21				
Human Resource Readiness	NGA	2.66	70.11	1582.50	.041	Reject	Significant
	LGU	2.43	56.81				
Organizational Readiness	NGA	2.68	70.84	1528.50	.021	Reject	Significant
	LGU	2.40	55.81				
Policy Environment	NGA	2.66	71.71	1330.50	.033	Reject	Significant
	LGU	2.33	54.62				
Overall	NGA	2.75	72.77	1486.50	.013	**Reject**	**Significant**
	LGU	2.36	52.14				

at .05 level of Sig.

Table 6 presents the result of the analysis using the Mann Whitney U-test, which is a non-parametric test, indicates that there is enough evidence to claim that there exists a significant difference in AI readiness in terms of technological readiness (U=1117.00, p<.001), human resource readiness (U=967.00, p<.001), organizational readiness (U=1095.50, p<.001), and policy environment (U=1051.50, p<.001), considering the position of the respondents. It is further confirmed by the overall U-value of 993.50, significant at <.001which is statistically lesser than the alpha of .05, thus, rejecting the null hypothesis. it can be gleaned that the rating provided by the administrators (Mean=2.91, Mean Rank=83.80) is statistically greater than the technical (Mean=2.39, Mean Rank=52.92).

Table 6 Significant Difference Between AI Readiness of NGAs and LGUs vis-à-vis Position

Variables	Group	Mean	Mean Rank	U	Sig.	Decision on H_o	Interpretation
Technological Readiness	Administrator	2.96	81.23	1117.00	<.001	Reject	Significant
	Technical	2.51	54.46				
Human Resource Readiness	Administrator	2.93	84.35	967.00	<.001	Reject	Significant
	Technical	2.35	52.59				
Organizational Readiness	Administrator	2.88	81.68	1095.50	<.001	Reject	Significant
	Technical	2.38	54.19				
Policy Environment	Administrator	2.86	82.59	1051.50	<.001	Reject	Significant
	Technical	2.31	53.64				
Overall	Administrator	2.91	83.80	993.50	<.001	**Reject**	**Significant**
	Technical	2.39	52.92				

at .05 level of Sig.

The gap is not limited to a single dimension but is pervasive. The widest disparity in mean ranks appears in Human Resource Readiness (Administrator Mean Rank (84.35) vs. Technical Mean Rank (52.59). This suggests that while Administrators may believe the organization has the necessary human capital, Technical staff—who would be directly responsible for coding, maintaining, and training on AI systems—feel a significant shortfall in skills, specialized training, and perhaps adequate staffing levels.

The differences in Technological Readiness (Administrator Mean Rank (81.23) vs. Technical Mean Rank (54.46) and Organizational Readiness (Administrator Mean Rank (81.68) vs. Technical Mean Rank (54.19) further elaborate on this. The perception of the Policy Environment (Administrator Mean Rank (82.59) vs. Technical Mean Rank (53.64) is also significantly different, indicates a statistically significant discrepancy, implying that ethical personnel perceive the current policies, regulations, or ethical guidelines as either insufficiently detailed, ambiguous or impractical for application within a technical context.

Table 7 presents the result of the analysis using the Kruskal Wallis H-test, which is a non-parametric test, indicates that there is enough evidence to claim that there exists a significant difference in AI readiness in terms of technological readiness (H(4)=21.82, p<.001), human resource readiness (H(4)=25.14, p<.001), organizational readiness (H(4)=25.12, p<.001), and policy environment (H(4)=26.69, p<.001), considering the year in service of the respondents. It is further confirmed by the overall H-value of 26.68, significant at <.001which is statistically lesser than the alpha of .05, thus, rejecting the null hypothesis.

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Table 7 Significant Difference Between AI Readiness of NGAs and LGUs vis-à-vis Year of Service

Variables	Group	Mean	Mean Rank	H	Sig.	Decision on H_o	Interpretation
Technological Readiness	Less than 1 year	3.11	90.38	21.82	<.001	Reject	Significant
	1 to 5 years	2.53	55.33				
	6 to 10 years	2.46	52.57				
	11 to 15 years	2.90	79.00				
	More than 15 years	3.18	92.94				
Human Resource Readiness	Less than 1 year	3.03	87.31	25.14	<.001	Reject	Significant
	1 to 5 years	2.38	55.14				
	6 to 10 years	2.33	50.53				
	11 to 15 years	2.87	81.98				
	More than 15 years	3.18	98.88				
Organizational Readiness	Less than 1 year	3.02	88.27	25.12	<.001	Reject	Significant
	1 to 5 years	2.35	53.22				
	6 to 10 years	2.43	55.17				
	11 to 15 years	2.80	78.64				
	More than 15 years	3.18	102.94				
Policy Environment	Less than 1 year	2.97	86.58	26.69	<.001	Reject	Significant
	1 to 5 years	2.33	55.15				
	6 to 10 years	2.27	50.09				
	11 to 15 years	2.87	82.93				
	More than 15 years	3.10	99.13				
Overall	Less than 1 year	3.11	90.38	26.68	<.001	**Reject**	**Significant**
	1 to 5 years	2.53	55.33				
	6 to 10 years	2.46	52.57				
	11 to 15 years	2.90	79.00				
	More than 15 years	3.18	92.94				

at .05 level of Sig. (df=4)

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Further analysis using the Bonferroni test, which is a post-hoc analysis statistics indicates that the significant difference is found the responses of those with less than 1 year in service (Mean=3.11, Mean Rank=90.38) is compared to those with 1 to 5 years (Mean=2.53, Mean Rank=55.33), and 6 to 10 years (Mean=2.46, Mean Rank=57.57). The data indicates a significant difference in Artificial Intelligence (AI) readiness across all its dimensions when public sector employees are grouped according to their year in service. The Kruskal-Wallis H-test, a non-parametric test used for comparing multiple independent groups, consistently produced highly significant *p*-values ($p<.001$) across all readiness dimensions, leading to the rejection of the null hypothesis and confirming the influence of employee tenure on AI readiness. Specifically, the mean ranks and mean scores show a U-shaped or polarization trend, where respondents with less than 1 year and more than 15 years of service exhibit the highest levels of AI readiness, while those in the 1 to 10 years of service groups report the lowest readiness. This is particularly evident in the post-hoc analysis, which found a significant difference when comparing the high readiness of the "less than 1 year" group to the lower readiness of the "1 to 5 years" and "6 to 10 years" groups.

Table 8 Significant Difference Between AI Readiness of NGAs and LGUs vis-à-vis Level of Involvement

Variables	Group	Mean	Mean Rank	H	Sig.	Decision on H_o	Interpretation
Technological Readiness	No Involvement	2.80	65.78	5.85	0.12	Failed to Reject	Not Significant
	Minimal Involvement	2.52	57.57				
	Moderate Involvement	2.73	67.35				
	High Involvement	2.99	80.68				
Human Resource Readiness	No Involvement	2.69	71.83	5.11	0.16	Failed to Reject	Not Significant
	Minimal Involvement	2.44	58.32				
	Moderate Involvement	2.59	65.38				
	High Involvement	2.84	79.82				
Organizational Readiness	No Involvement	2.51	61.78	5.77	0.12	Failed to Reject	Not Significant
	Minimal Involvement	2.44	57.58				
	Moderate Involvement	2.65	68.45				
	High Involvement	2.81	79.94				
Policy Environment	No Involvement	2.58	69.22	7.33	0.06	Failed to Reject	Not Significant
	Minimal Involvement	2.39	57.58				
	Moderate Involvement	2.54	64.65				
	High Involvement	2.88	85.65				
Overall	No Involvement	2.69	73.06	7.69	0.06	**Failed to Reject**	**Not Significant**
	Minimal Involvement	2.48	57.74				

	Moderate Involvement	2.61	65.88				
	High Involvement	2.81	76.29				

at .05 level of Sig. (df=3)

Table 8 presents the result of the analysis using the Kruskal Wallis H-test, which is a non-parametric test, indicates that there is not enough evidence to claim that there exists a significant difference in AI readiness in terms of technological readiness (H(3)=5.85, p=0.12), human resource readiness (H(3)=5.11, p=0.16), organizational readiness (H(3)=5.77, p=0.12), and policy environment (H(3)=7.33, p=0.06), considering the involvement of the respondents. It is further confirmed by the overall H-value of 7.69, significant at 0.06 which is statistically greater than the alpha of .05, thus, failing to reject the null hypothesis.

The analysis, based on a Kruskal-Wallis H-test, indicates no statistically significant difference in the overall Artificial Intelligence (AI) Readiness of National Government Agencies (NGAs) and Local Government Units (LGUs) when grouped according to their Level of Involvement (No, Minimal, Moderate, High Involvement). This finding holds true across all four dimensions of AI readiness. The overall result (H(3)=7.69, p=0.06) further confirms the failure to reject the null hypothesis at the (0.05) level of significance, suggesting that the degree to which an agency is involved does not translate into a statistically distinct level of perceived AI readiness. While the mean rank and mean scores for overall readiness and its dimensions consistently increase from "Minimal Involvement" to "High Involvement", this observed upward trend is not substantial enough to be deemed a statistically reliable difference in the broader population.

Table 9 reflects that the AI adoption of NGAs and LGUs in terms of technological adoption (Mean=2.58, SD=0.68) is good. It is shown that in terms of technological adoption, the highest mean is found in indicator 1 (Mean=2.66, SD=0.70) and the lowest is found in indicator 2 and 4 (Mean=2.54, SD=0.74), both indicating agreement among the respondents. This finding suggests a positive orientation towards the implementation of AI technologies within the public sector, consistent with the global push for Digital Government Transformation driven by the pursuit of efficient and transparent public services.

Table 9 Level of AI Adoption among NGAs and LGUs in terms of Technological Adoption

Variables	AWM	SD	DI	Rank
1. Our agency/LGU currently uses AI tools or systems in its operations.	2.66	0.70	Agree	1
2. AI technologies have improved the efficiency and accuracy of our service delivery.	2.54	0.74	Agree	4.5
3. The integration of AI has automated some of our organizational processes.	2.60	0.72	Agree	2
4. Our information systems are capable of supporting AI applications.	2.54	0.74	Agree	4.5
5. We continuously explore new AI solutions to enhance our operations.	2.58	0.78	Agree	3
Average Weighted Mean	**2.58**	**0.70**	**Agree**	

Legend: 3.25-4.00 Strongly Agree (Excellent); 2.50-3.24 Agree (Good);1.75-2.49 Moderately Agree (Fair); 1.00-1.74 Strongly Disagree (Poor)

The highest rated variable, "*Our agency/LGU currently uses AI tools or systems in its operations*" (Mean=2.66, SD=0.70), confirms a nascent but established presence of AI applications. Consistent with Rogers' (2003) Diffusion of Innovation (DOI) theory, this trend indicates that the adoption phase has begun within specific sectors, namely NGAs and LGUs. Currently, this integration appears concentrated on "narrow" or "weak" AI applications, including automated workflows, citizen-facing chatbots, and task-specific data analysis tools. This observation is reinforced by the moderately high rating for AI-driven process automation (Mean=2.60, SD=0.72), which underscores the established advantages of AI in optimizing administrative functions and minimizing manual labor to boost bureaucratic productivity (Wirtz et al., 2020). The continuous exploration of new AI solutions (Mean=2.58, SD=0.78) points to an innovative culture and leadership support in the public sector, which are identified as key organizational drivers for successful AI adoption, according to studies by the Joint Research Centre (2024). The relatively low mean scores for AI efficiency (Mean=2.54) and system support (Mean=2.54) suggest that while AI adoption is underway, organizational infrastructure has not yet matured to fully realize its benefits.

Table 10 Level of AI Adoption among NGAs and LGUs in terms of Human Capability and Competence

Variables	**AWM**	**SD**	**DI**	**Rank**
1. Our personnel have adequate knowledge and understanding of AI technologies.	2.39	0.77	Moderately Agree	4
2. The organization provides regular training or seminars on AI and related technologies.	2.35	0.78	Moderately Agree	5
3. Employees are confident in using AI-enabled tools in their work.	2.45	0.79	Moderately Agree	2
4. Our agency/LGU has technical experts capable of developing or maintaining AI systems.	2.42	0.82	Moderately Agree	3
5. Staff are encouraged to improve their digital and analytical skills for AI applications.	2.48	0.82	Moderately Agree	1
Average Weighted Mean	2.42	0.79	Moderately Agree	

Legend: 3.25-4.00 Strongly Agree (Excellent); 2.50-3.24 Agree (Good);1.75-2.49 Moderately Agree (Fair); 1.00-1.74 Strongly Disagree (Poor)

Table 10 reveals that the overall AI adoption of National Government Agencies (NGAs) and Local Government Units (LGUs) in terms of Human Capability and Competence is rated as Fair indicates a critical area for improvement, as the human element is fundamental to successful technology integration. The relatively low composite mean suggests that government agencies generally acknowledge the need for a skilled workforce but are not yet fully equipped or confident in leveraging Artificial Intelligence (AI) technologies. The most agreed-upon indicator is the encouragement of staff to improve their digital and analytical skills for AI applications (Mean = 2.48, SD = 0.82), which, while positive, still falls just below the threshold for an "Agree" rating and is consistent with the global emphasis on upskilling and reskilling the public workforce to avoid job displacement and remain effective in an AI-intensive economy (Khogali & Mekid, 2023). This perceived willingness of employees, however, contrasts with the lower mean for the provision of regular training or seminars on AI and related technologies (Mean = 2.35, SD = 0.78), which is the lowest indicator, suggesting a potential gap between organizational encouragement and concrete support through capacity-building initiatives.

The "Fair" rating for human capability highlights the difficulties identified within the Technology–Organization–Environment (TOE) framework as articulated by Tornatzky and Fleischer (1990). In this context, internal organizational attributes, such as human capital and organizational culture, play a pivotal role in shaping the processes of technology adoption. The prevailing assessment identified as "Moderately Agree" regarding expertise, training, and confidence indicates a deficiency in robust in-house expertise and digital competencies, which are essential factors in facilitating the adoption of artificial intelligence (European Union, 2024). The observed moderate level of agreement regarding the possession of adequate knowledge and the availability of technical experts (Mean scores of 2.39 and 2.42, respectively) indicates that, although foundational elements are in place, they remain inadequate.

Table 11 indicates a "Fair" level of artificial intelligence adoption pertaining to organizational support within National Government Agencies (NGAs) and Local Government Units (LGUs), as demonstrated by a composite mean of 2. 49, SD = 0.80. This moderate level of consensus indicates that, despite the initiation of foundational efforts, the organizational milieu continues to contend with substantial resource limitations and strategic constraints. The descriptive classification of "Fair" signifies a pivotal threshold; the existing levels of support are positioned just below "Good" (Agree), thereby emphasizing a strategic priority for organizations aiming to progress from initial readiness to thorough, full-scale implementation.

Table 11 Level of AI Adoption among NGAs and LGUs in terms of Organizational Support

Variables	AWM	SD	Descriptive Interpretation	Rank
1. Top management actively promotes AI adoption within the organization.	2.50	0.80	Agree	2
2. Adequate financial and logistical support is provided for AI-related projects.	2.46	0.80	Moderately Agree	5
3. There is a clear organizational strategy for implementing AI initiatives.	2.47	0.76	Moderately Agree	3.5
4. Our organization collaborates with external partners (academia, private sector, or other LGUs/NGAs) in AI development.	2.57	0.79	Agree	1
5. The organization recognizes and rewards innovation efforts related to AI.	2.47	0.82	Moderately Agree	3.5
Average Weighted Mean	**2.49**	**0.80**	**Moderately Agree**	

Legend: 3.25-4.00 Strongly Agree (Excellent); 2.50-3.24 Agree (Good);1.75-2.49 Moderately Agree (Fair); 1.00-1.74 Strongly Disagree (Poor)

The highest mean score was found in the indicator, "Our organization collaborates with external partners (academia, private sector, or other LGUs/NGAs) in AI development," which was rated as Agree (Mean = 2.57, SD = 0.79). This highlights that collaboration is the strongest organizational enabler for AI adoption among NGAs and LGUs.

The variable with statement "Adequate financial and logistical support is provided for AI-related projects" yielded the lowest mean score, with a descriptive interpretation of "Moderately Agree" (Mean = 2.46, SD = 0.80). The substantial agreement regarding the provision of financial support, alongside a comparable assessment of the clarity of the organizational strategy (Mean = 2.47), indicates that although there may exist a degree of willingness to invest, there is a notable deficiency in strategic alignment and significant initial investments requisite for transcending isolated artificial intelligence experimentation.

Table 12 presents the AI adoption of NGAs and LGUs in terms of Policy Environment. The data indicates a Fair level of Artificial Intelligence (AI) adoption among National Government Agencies (NGAs) and Local Government Units (LGUs) concerning the Policy Environment. The composite mean of 2.43 and SD = 0.81 falls within the Moderately Agree range of 1.75-2.49. This data suggests that respondents generally perceive the policy landscape as having moderate, rather than strong, support for AI adoption. A rating of "Moderately Agree" indicates that the compatibility of the policy environment is at a moderate level.

Table 12 Level of AI Adoption among NGAs and LGUs in terms of Policy Environment

Variables	AWM	SD	DI	Rank
1. The existing government policies in my agency are sufficient to support the adoption of AI technologies.	2.43	0.79	Moderately Agree	4
2. Current ethical and legal frameworks adequately address data privacy, transparency, and accountability in the use of AI within the public sector.	2.46	0.82	Moderately Agree	1
3. Our agency has adequate technical infrastructure and skilled personnel to effectively implement AI-driven programs and services.	2.39	0.83	Moderately Agree	5
4. There are clear and supportive policy guidelines that minimize barriers to AI adoption in public governance.	2.44	0.79	Moderately Agree	2.5
5. Our agency demonstrates a strong commitment to developing policies that promote responsible and efficient AI adoption in public governance.	2.44	0.81	Moderately Agree	2.5
Average Weighted Mean	**2.43**	**0.81**	**Moderately Agree**	

Legend: 3.25-4.00 Strongly Agree (Excellent); 2.50-3.24 Agree (Good);1.75-2.49 Moderately Agree (Fair); 1.00-1.74 Strongly Disagree (Poor)

An examination of the Policy Environment domain reveals a multifaceted challenge: a distinct divergence between institutional discourse and functional capacity. Empirical findings show that the perceived adequacy of existing ethical and legal frameworks—specifically those governing data privacy, transparency, and accountability—attained the highest mean score of 2.46 (SD = 0.82). In contrast, the fundamental "gears" of the system—technical infrastructure and human capital—recorded the lowest mean score of 2.39 (SD = 0.83).

Table 13 Summary of Level of AI Adoption Among NGAs and LGUs

Variables	AWM	SD	Descriptive Interpretation	Rank
Technological Adoption	2.58	0.75	Agree	1
Human Capability and Competence	2.42	0.79	Moderately Agree	4
Organizational Support	2.49	0.80	Moderately Agree	2
Policy Environment	2.43	0.81	Moderately Agree	3

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Composite Mean	**2.48**	**0.80**	**Moderately Agree**	

Legend: 3.25-4.00 Strongly Agree (Excellent); 2.50-3.24 Agree (Good);1.75-2.49 Moderately Agree (Fair); 1.00-1.74 Strongly Disagree (Poor)

Table 13 reveals the summary of AI adoption among the National Government Agencies (NGAs) and the Local Government Units (LGUs). The data shows that the overall adoption level is described as "Fair" (Mean=2.48, SD=0.80). The data suggests that while both NGAs and LGUs have begun integrating AI, their progress is moderate and signifies a phase of cautious experimentation rather than full-scale institutionalization. A detailed breakdown of the domains highlights a significant imbalance: Technological Adoption achieved the highest rating (Mean=2.58, SD=0.75) and is the only domain classified as "Agree" (Rank=1). This strongly suggests that public sector agencies perceive the necessary technology (e.g., platforms, tools, and basic infrastructure) as relatively available, compatible, or offering a clear advantage, aligning with the "Technology" context of the Technology-Organization-Environment (TOE) Framework (Tornatzky & Fleischer, 1990). However, the other three domains—Organizational Support (Mean=2.49, Rank=2), Policy Environment (Mean=2.43, Rank=3), and particularly Human Capability and Competence (Mean=2.42, Rank=4)—are all categorized as "Fair".

Table 14 Significant Relationship between AI Readiness and Adoption

Variable 1	**Variable 2**	***r***	**Sig.**	**Decision on H_o**	**Interpretation**
AI Readiness	**AI Adoption**	.704**	<.001	Reject	Significant

Legend: r: ±0.80-1.0 Very Strong; ±0.60-0.79 Strong; ±0.40-0.59 Moderate; ±0.20-0.39 Weak; ±0.00-0.19 Very Weak

Table 14 presents the result of the analysis using Pearson's Correlation which shows that there exists a significantly strong relationship between AI Readiness and AI Adoption (r_s=(125) .704**, p<.001), as provided by the p-value of less than the alpha of .05, thus rejecting the null hypothesis. The significant positive correlation suggests that entities exhibiting a higher degree of preparedness, as indicated by elevated levels of AI Readiness, are markedly more inclined to adopt and implement AI technologies, reflecting a greater propensity for AI Adoption. The relationship was determined to be statistically significant, as indicated by a p-value of less than 0.001 This value is considerably below the conventional significance threshold of α = 0.05, thereby providing robust evidence to reject the null hypothesis positing that no relationship exists between the two variables. The findings indicate that initiatives aimed at enhancing organizational readiness serve as critical prerequisites for the successful adoption of artificial intelligence technologies.

As part of output of this research, a strategic intervention program is proposed aimed at enhancing AI readiness and governance is formulated through a comprehensive, multi-faceted framework that seeks to address systemic deficiencies identified across four foundational dimensions: technological, human resources, organizational structures, and policy environments. The primary objective is to develop a comprehensive and pragmatic roadmap that effectively aligns strategic objectives with operational realities.

Technological Foundations and Data Governance

To enhance the technological infrastructure, the program necessitates a systematic upgrade of infrastructure and the implementation of shared services, with a particular focus on local government units (LGUs). This initiative is designed to mitigate the substantial disparity in technological preparedness identified between national and local government entities. This endeavor entails the provision of centralized and shared cloud computing resources, along with technical assistance, aimed at mitigating the significant upfront cost barriers faced by local administrations.

Human Capability and Competence

The strategy prioritizes the enhancement of human capability and competence through the implementation of Targeted and Differentiated Upskilling Programs, applicable across all career levels. A primary area of emphasis is the Mid-Career Core, encompassing individuals with 1 to 10 years of experience, who presently exhibit the lowest readiness scores. The development of targeted training programs is essential to enhance both their technological and human resource readiness. Administrators and leaders will undergo training programs focused on digital leadership, governance, and ethical oversight to facilitate a more constructive relationship with technical staff, thereby bridging the existing perception gap.

Organizational Support and Culture

To enhance organizational support and foster a cohesive culture, the proposed intervention emphasizes the necessity of establishing a formalized Artificial Intelligence (AI) Strategy and a structured Budget Allocation framework. This approach aims to transition from isolated pilot initiatives to institutionalized programs, which constitutes a critical focal point for both Administrators and Senior Management. Improving Administrative Digital Leadership is essential for bridging the considerable disparity in perceived readiness between optimistic administrators and more cautious technical personnel.

Policy Environment and Governance:

Finally, to institutionalize responsible AI governance, which is a high-leverage area due to its strong correlation with AI adoption, the strategy requires the implementation of Robust Monitoring and Evaluation (M&E) Mechanisms for AI projects. To institutionalize this governance framework, it is essential to implement robust monitoring and evaluation (M&E) mechanisms specifically tailored for AI projects. This statement highlights that monitoring and evaluation (M&E) and data privacy compliance are identified as among the lowest-rated indicators. The strategy further necessitates the implementation of explicit and actionable ethical and regulatory frameworks, which serve to convert overarching policy directives into distinct operational guidelines for technical teams.

CONCLUSION

The public sector is positioned in the early-to-middle stages of AI adoption, showing foundational technological capacity but struggling to institutionalize the necessary human, organizational, and policy safeguards for widespread integration. The overall readiness is "Good," but adoption is only "Fair," demonstrating that readiness has not fully translated into successful, scaled adoption.

Readiness is unevenly distributed. A critical and statistically significant digital divide exists, placing NGAs as Early Adopters and many LGUs as Late Majority/Laggards due to severe resource, infrastructure, and human capital asymmetries. The Governance Gap is the Primary Constraint. Despite high technological potential, the lowest-rated aspects of both Readiness and Adoption concern cybersecurity, monitoring/evaluation, and compliance with ethical/policy guidelines. This signals that while government is technologically ready to experiment, it is not yet institutionally prepared for responsible and accountable scaling of AI.

The Workforce Needs Targeted Investment. The significant perceptual gap between Administrators (optimistic) and Technical Staff (conservative/pragmatic), coupled with the skills gap in the mid-career core, indicates a failure to align strategic vision with operational reality. Successful adoption requires unified, role-specific capacity-building to move employees from minimal to active engagement.

Policy and Organizational Will are Critical Accelerators: The findings confirm that while technology is a necessary pillar, robust policy frameworks and strong organizational support (leadership, budget) are the key factors for translating existing readiness into measurable and sustained AI adoption.

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