Applied Mathematics & Information Sciences
An International Journal

http://dx.doi.org/10.18576/amis/190302

Analyzing AI Readiness through Digital Transformation and Data Management: A Case Study of Qatar's Government Sector

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Received: 11Nov. 2024, Revised: 12 Dec. 2024, Accepted: 26 Jan. 2025
Published online: 1 May 2025.

Abstract: This paper investigates the Artificial Intelligence (AI) readiness of government institutes, focusing on the criteria of the two critical areas of Digital Transformation and Data Management. We conduct interviews with 21 Information Technology directors (CIO) across various national government institutes and develop a comprehensive decision support index for assessing the readiness of government entities for AI adoption in their operations. The maturity of digital transformation includes strategy and vision, innovation, and service development. Data management practices such as data governance, data quality, data Privacy and Ethics. We calculate individual and aggregate TRL scores to estimate the overall AI readiness score for the case of government sectors in Qatar. The research contributes to the literature on AI readiness in public sector organizations by applying a combination of the Simple Additive Weighting (SAW) method and the Technology Readiness Level (TRL) framework to evaluate readiness across multiple dimensions. The primary objective of this study is to deepen the understanding of an organization's progression towards AI adoption. The findings offer insights for policymakers and organizational leaders in similar contexts, providing a framework and a roadmap for improving AI readiness. The study underscores the importance of a comprehensive approach to AI adoption, considering technological capabilities and strategic alignment, resource allocation, and skill development. The paper shows a framework for a purposeful decision in the AI adoption process for government organizations by identifying key readiness factors and their impact on AI adoption.

Keywords: Simple Additive Weighting (SAW), Technology Readiness Level (TRL), AI-readiness Adoption, maturity level assessment in Government organization, Digital Transformation, Data Management.

1. Introduction

The concept of organizational readiness for change is a vital precursor to any form of organizational transformation including the adoption of Artificial Intelligence (AI). It has garnered considerable attention in contemporary research [1]. AI is a term coined in 1955 and has become prominent due to the recent global technological revolution, evolving as a form of non-human intelligence designed to execute specific tasks and activities (Dwivedi et al., 2019 as cited in [1]). The diversification of AI studies has led to a wide understanding of its capabilities and applications, significantly affecting modern organizational practices and structures [3], [4].

In the field of management, AI is characterized by its ability to interpret external data, learn from it, and use these insights to achieve specific goals (Kaplan & Haenlein, 2019 as cited in [2]). This growing technology is not only integrating into various organizational practices but also reshaping human-machine interactions, thus playing a pivotal role in the digital transformation of organizations [2]. However, AI's inherent complexity presents unique challenges for organizations, emphasizing the need for a thorough evaluation of readiness to harness its full potential [1].

The shift towards AI adoption is increasingly noticeable not just at the federal or national government level, but also within state and local governments (Engstrom et al. 2020; Kuziemski and Misuraca 2020 as cited in [5]. Local government agencies, often constrained by limited resources and direct public interactions, face distinct challenges in adopting AI technologies. Yet, research exploring how these government levels are adapting to AI remains limited, particularly in understanding the perspectives of government leadership on AI systems (Matibag 2020; Wang et al. 2020 as cited in [3]). The theory of organizational readiness for change suggests that higher levels of readiness can significantly enhance the success of ‘innovation’ adoption while minimizing the risk of failure (Snyder-Halpern 2001; Weiner 2009 as cited in [4]). Readiness encompasses both psychological and structural aspects, including commitment to change and the capacity for transformation. However, consensus on the most relevant factors for AI readiness is lacking, underscoring the need for context-specific models tailored to specific technological domains (Nguyen et al. 2019; Molla and Licker 2005 as cited in [4]).

This strong trend towards digital innovation in Qatar was

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certainly a motivator for studying pillars, factors, and catalysts of introducing AI into the public sector being the core of the digital agenda in addition to the position of the author in the government.

Given this backdrop, our study seeks to delve into the critical factors that define organizational AI readiness, particularly for government organizations, and how these factors influence the AI adoption process. By addressing this gap, we aim to contribute to both theoretical understanding and practical application in the topic of AI readiness and adoption within governmental contexts ([4]; [5]). In this research, AI-readiness in government institutes categorized into two areas: digital transformation [6], and Data Management [7]. Literature Review

Artificial Intelligence (AI), as defined by Kaplan & Haenlein (2019), is a system's ability to interpret external data, learn from it, and use those learnings to achieve specific goals through flexible adaptation [8]. The nature of AI as a disruptive innovation has been emphasized, highlighting its potential to transform organizational operations and decision-making processes (Agrawal et al., 2018; Davenport, 2018; Dwivedi et al., 2019 as cited in [4]). This transformation is particularly significant in government sectors where AI adoption can enhance public service delivery, augmenting the quality of life for citizens (Catalyst Fund 2020; Provost and Fawcett 2013 as cited in [4]).

2. AI Readiness and Adoption

AI readiness, a concept growing in importance, involves preparing organizations for successful AI integration. It encompasses building capabilities and aligning organizational processes with AI technologies (Alsheibani et al. 2019; Baier et al. 2019; Gallivan 2001 as cited in [8]). The factors influencing AI readiness have been identified as strategic alignment, resources, knowledge, culture, and data, each with specific action fields (Pumplun et al. 2019 as cited in [4]). These readiness factors are essential for organizations to effectively leverage AI's business value, given its complex nature and the challenges associated with its deployment (Lokuge et al. 2018 as cited in [4]). The readiness approach plays a pivotal role in the discourse surrounding AI, as it casts light on adoption as a dynamic and ongoing process. This perspective is crucial for understanding the challenges many organizations face in deploying AI beyond limited, isolated applications and in sustaining its use over the long term. By focusing on readiness, we can start to unravel the various factors that contribute to these difficulties [[8]].

Examining readiness in AI adoption helps identify the specific stages where organizations encounter obstacles, whether during initial implementation, integration into existing systems or in scaling and maintaining AI solutions. This approach also encourages a deeper look into organizational culture, resources, skill levels, and strategic alignment, all of which are critical in determining the success of AI initiatives [[8]]. Moreover, understanding readiness not just as a preliminary step but as an ongoing requirement can lead to the development of better support systems and frameworks. These would aid organizations not only in adopting AI initially but also in adapting to its evolving nature and the changing business environment. Such comprehensive readiness frameworks could encompass continuous learning, iterative improvement, and flexibility, ensuring that AI adoption is sustainable and effectively contributes to long-term organizational goals.

Literature referred to multiple AI-readiness frameworks that encompass factors and components to gauge the AI-readiness within an organization, some of which were designed for certain industries such as manufacturing. The framework [3] emphasizes four essential dimensions of digital transformation to a sociotechnical AI status of the organization: technologies, activities, boundaries, and goals. Organizational AI Readiness Factors were identified by [1] to be: Strategic Alignment, Resources, Knowledge, Culture, Data, and Emerging Insights Beyond the AI Readiness Factors. Kelley identified eleven key factors under the framework of business code adoption theory that influence the successful implementation of AI principles within organizations. These factors include communication, management support, training, the presence of an ethics office or officer, a mechanism for reporting, enforcement practices, methods of measurement, related technical processes, adequate technical infrastructure, organizational structure, and an interdisciplinary approach [8].

3. AI in Government-Organizations

The integration of AI in government institutes introduces unique challenges. The process often involves changing existing workflows, upskilling employees, and addressing concerns related to data quality and privacy (Agrawal et al. 2018, Dattner et al. 2019, Tambe et al. 2018 as cited in [4]). Furthermore, government institutes must consider the compatibility of AI with their existing IT infrastructure and data management practices (Groopman 2018; Iansiti and Lakhani 2020; Kruse et al. 2019 as cited in [4]).

Several studies have shown that the adoption of modern technologies by individuals and companies can be significantly influenced by governments. These include regulations and support, the level of institutional quality, cultural influences, and the availability of skilled labor (Tornatzky and Fleischer 1990, Vagnani et al., 2019, Han and Park 2017 as cited in [9]). Additionally, the uptake of innovative technologies is often shaped by specific national initiatives aimed at fostering innovation. For instance, Germany and the U.S. have implemented strategies and programs to support intelligent manufacturing. In the U.S., initiatives like the 'Advanced Manufacturing Partnership' (2011) and 'Industrial Internet' (2012) have been influential, while Germany launched the 'Industry 4.0 Plan' (2013) [[9]]. These government-led initiatives not only provide financial and regulatory support but also create a conducive environment for innovation and adoption of modern technologies. They can lead to the development of infrastructure, policies, and educational programs that are essential for nurturing the necessary skills and knowledge base. Moreover, these initiatives can stimulate collaborations between academia, industry, and government, further driving technological advancements.

Governments are actively engaged not only in regulating AI and promoting AI innovation but also in incorporating this technology into public services. For example, the Republic of Korea is utilizing AI to enhance government functions via its Digital Platform Government initiative. In a similar vein, the UK's National Health Service is advancing research and innovation in new AI-based screening technologies for health and social care [[10]]. Out of thirteen developing countries in the MENA region, three - Egypt, Tunisia, and Jordan - have implemented their national AI strategies [[11]]. Nonetheless, grasping the most effective ways to adopt AI for the benefit of the public continues to be a complex issue. A government needs to possess a strategic vision for AI development and governance, complemented by suitable regulations and a focus on ethical considerations (governance and ethics). Additionally, the government needs to maintain a robust internal digital capacity, which includes the necessary skills and practices to adapt to emerging technologies [11].

4. Digital Transformation Components

Perceiving AI as a complex and advanced digital technology, its integration into an organization necessitates comprehensive technological groundwork initially (Alsheibani, Cheung, and Messom 2018 as cited in [12]). Therefore, adopting AI should be viewed as a progressive transformation process within the organization, rather than as a sudden leap in technology. This process requires effective digitization as a prerequisite, meaning the conversion of analog processes into digital formats[13]. In essence, organizations must lay a solid foundation in digital technologies and processes to successfully implement AI. [[12]]. Digital transformation in organizations, particularly in government institutes, is multifaceted. It includes components such as strategy and vision, innovation, service development, responsive operations, and supply chain management ([14]; [15]; [16]). The responsiveness of these components to digital transformation efforts, including AI adoption, is crucial for successful implementation and achieving organizational goals ([17]; [18]).

In governments, the effectiveness of implementing AI heavily relies on the availability of AI tools from the nation's technology sector. This sector must be sufficiently mature to meet government needs. Key elements include a high capacity for innovation, a business environment conducive to entrepreneurship, and substantial investment in research and development (R&D). The human capital aspect, encompassing the skills and education of professionals in this sector, is also of paramount importance [11].

Data management is a critical aspect of AI readiness. It involves ensuring data quality, accessibility, and the effective flow of data, which are necessary for training and deploying AI models [19]. Data-driven technologies might lead to basic or even flawed decisions if they are based on limited or incorrect data, as argued by Baryannis et al. (2019) as cited in [9]. Components of data management such as governance frameworks, quality management, and analytics play a pivotal role in the successful adoption of AI [20].

Big data lays the groundwork for real-time decision-making (Javaid et al. 2020 as cited in [12]), while learning-based algorithms enhance a firm's data analytics capabilities. Consequently, AI technologies and systems boost the information processing capacity of companies (Belhadi et al. 2021; Dubey et al. 2021 as cited in [12]). This enhanced capacity enables firms to withstand and recover from unforeseen disruptive events, thereby bolstering their overall resilience (Heinicke 2014 as cited in [12]) more effectively. Industrial Big Data, a term introduced by Mourtzis et al. (2016) as cited in [9], refers to the vast data pools generated in the modern industrial landscape through sensor-equipped machinery, cloud-based systems, and interconnected machines and resources. In recent times, the growth in the availability of industrial Big Data technologies, coupled with advancements in computing power and enhanced machine learning techniques and algorithms, has broadened the scope for integrating AI technologies in manufacturing settings, as highlighted in the works of Duan et al. (2019) and the National Science and Technology Council (2016) as cited in [9]. For AI tools to function optimally, they require access to abundant, high-quality data (data availability). To minimize biases and errors, this data must accurately represent the citizenry of the country (data representativeness). Furthermore, realizing the full potential of this data is contingent upon having the necessary infrastructure to power AI tools and ensure their accessibility to citizens [[10]].

5. Data Collection

To collect the data, interviews were conducted with IT Directors from 21 out of 34 government organizations in Qatar, representing approximately 61% of the country's government bodies. The objective was to guarantee that participants had a comprehensive understanding and the necessary decision-making power concerning IT Directors in their organizations. In separate sessions, these IT directors were requested to assess the Criteria of Digital Transformation Maturity and Data Management Maturity in their organizations. Nine distinctive Criteria were evaluated in each area. The validated Criteria of DTM as mentioned in [6] are: Strategy and Vision, Innovation and Services Development, Experience Centric Design, Responsive Operations and Supply Chain, Funding and Resource Allocation, Culture, Talent and Skills, Infrastructure, and Security and Risk Management. The Criteria of DMM included as mentioned in [7]: Data governance, Data quality management, data integration and interoperability, Data analytics and business intelligence, Data privacy and ethics Compliance, training and skill development, data governance communication, Data governance implementation costs, and data access and sharing policies. Questions were asked for each criterion to account for the organization's capability. The IT Directors evaluated each criterion on a scale ranging from 1 to 10. In this scale, '1' signifies the lowest level of maturity, while '10' denotes the highest level of maturity.

In assessing the application of digital transformation within their organizations, the IT Directors were asked to evaluate several key areas. For instance, they were requested to reflect on their organization's 'Strategy and Vision.' This included consideration of the vision and mission, evaluation of procedures, management of stakeholders, and the alignment of policies with advanced technology. Another focus topic was 'Innovation and Services Development,' where Directors were asked about their investment in technological experimentation, fostering innovation, and evaluating the impacts of implementation during the innovation process. In addition, they were asked about 'Experience Centric Design,' encompassing user (customer or citizen) experience, user interface (UI) design, understanding user needs and expectations, delivery and operations, and process optimization.

The Directors were also queried on the maturity level of data management within their organizations. For example, an aspect under consideration was 'Data Governance,' which involved questions about policies and standards, roles and responsibilities, data definitions, data lifecycle management, change management, metrics and monitoring, and the functioning of data governance committees. Another aspect was 'Data Quality Management,' where the Directors were prompted to evaluate data profiling, data cleansing, data validation, data standardization, data enrichment, data monitoring and auditing, and the use of data quality tools. Moving on, the discussion tackled 'Data Privacy and Ethics Compliance,' covering topics such as consent, transparency, data minimization, security measures, accountability, bias mitigation, and data ownership. A sample of the collected data is illustrated on the table in Appendix A.

6. Materials and Methods

Decision-making is crucial in management for selecting the best option from available alternatives. It often involves evaluating various options against a set of criteria, falling under the umbrella of multi-criteria decision-making MCDM [21]; [22]. Various methodologies assist decision-makers in evaluating options to make informed choices. This involves analyzing the attributes of multiple alternatives and selecting one or more based on the decision-maker's criteria, values, and preferences. Decision-making challenges typically involve various decision variables and criteria that must be considered [16].

6.1 SAW (simple additive weighting):

SAW (Simple Additive Weighting) is an MCDM method used to analyze the set of alternatives to choose one or more according to certain criteria, values, and preferences determined by decision-maker [23]. It is recognized to be one of the preferred techniques for decision-making as it is a straightforward approach. It aggregates decision variables by their weights to reflect their importance. This method requires the use of fundamental arithmetic as in addition and multiplication which consequently requires the values used in the equations to be numerical[23].

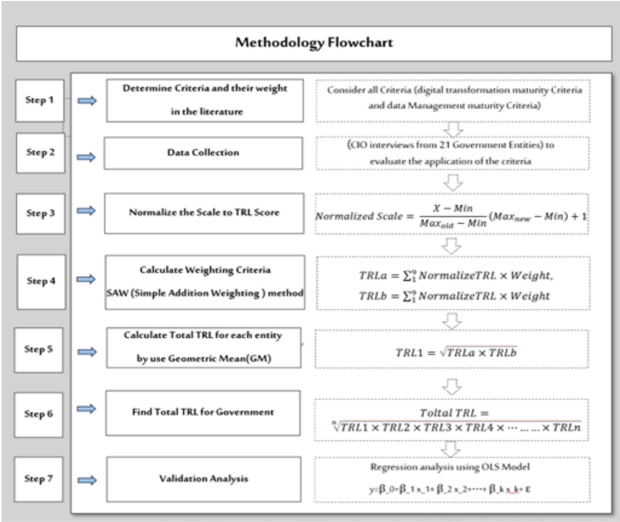
6.2 TRL (Technology Readiness level)

Technology Readiness Levels (TRLs), originally developed by NASA, are recognized universally as a standard for assessing the progress of technology [24]. This widely adopted measure is an integral part of systems engineering and managing technology. The TRL framework, consisting of nine levels, offers a systematic method to evaluate the development stage of various technologies. It provides a uniform basis for comparing the maturity levels of diverse types of technologies, including materials, hardware, software, and devices [24]. On the other hand, the TRL framework provides a structured way to evaluate and categorize the maturity of technologies, from conceptual stages to full deployment as illustrated in Table 2. In the domain of AI, where technologies can range from nascent algorithms to fully developed systems, the TRL offers an understanding of where a particular technology stands in its development journey [8].

In this research, we introduce an innovative approach by integrating the multi-criteria decision support model SAW, which evaluates and ranks entities based on their performance across various criteria, with the Technology Readiness Level (TRL) framework. This combination aims to provide a thorough assessment method, enhancing the decision-making process by considering both quantitative metrics and technological maturity levels. This approach allows for a comprehensive understanding of the readiness factors and the challenges in AI adoption, particularly in the context of government institutes ([25]; [2]; Shrestha, Ben-Menahem, & Krogh, 2019 as cited in [26]).

This research utilizes the (TRLs) score as a key indicator to assess the advancement of AI projects towards adoption as it aptly addresses the diverse range of AI technologies, each at varying stages of readiness. TRLs are employed to assess the AI-readiness of government -organizations in Qatar based on 18 criteria, digital transformation [6] and data management maturity, collectively forming the criteria for AI readiness. It draws on interview data gathered from the Directors leading the IT departments in 21 government institutes.

Table 1: Methodology Flowchart



Step 1: Determine The Criteria and Their Weight: Digital transformation criteria as mentioned in [6] were considered and Data Management [7] being major prerequisites for introducing AI into government organizations. The study offers a Framework to dive into the specific issues and challenges that emerge at various stages of the adoption process by adopting a qualitative approach. This method allows for a detailed exploration of the complexities inherent in the journey towards integrating AI within organizational contexts [8]. The model was created to map the two dimensions - Digital Transformation Maturity DTM and Data Management Maturity DM - using SAW in terms of Technology Readiness Levels (TRLs) from 1 to 9. As illustrated in Table 2:

Table 2: TRL framework [8] in context of AI readiness

○TRL 1-3 (Early Stage)	• DTM: Low - Initial digital capabilities and infrastructure. • DM: Low - Basic data collection, limited integration, and analysis capabilities.
○TRL 4-6 (Development Stage):	• DTM: Medium - Developing digital capabilities, better infrastructure, beginning to integrate digital solutions. • DM: Medium - Improved data quality, integration, beginning of analytics use.
○TRL 7-9 (Advanced Stage)	• DTM: High - Advanced digital capabilities, fully integrated digital solutions, strong leadership in digital transformation. • DM: High - Advanced data analytics capabilities, robust data governance, high-quality and accessible data.

Each TRL stage can be defined as a combination of DTM and DM. For example:

TRL 1: DTM-Low and DM-Low.

TRL 4: DTM-Medium and DM-Low to Medium.

TRL 7: DTM-High and DM-Medium to High.

TRL 9: DTM-High and DM-High.

Mapping DTM and DM into the TRLs scale enables the visualization of a more nuanced and comprehensive view of an organization's readiness for AI implementation.

Step 2: Data Collection: the Interviews were held with IT directors from 21 government -organizations in Qatar. They assessed their organizations based on nine criteria for Digital Transformation Maturity (DTM), and 9 criteria in data Management Maturity (DM). Each criterion was rated on a scale from 1 to 10, where 1 is the lowest maturity level and 10 is the highest.

Step 3: Normalization: The results from each session were combined in preparation for the normalization process using equation (1). Normalization was necessary to set the (1-10) scale to suit the 9 scaled TRLs.

$$\boldsymbol{Normalized\ Scale} = \frac{\boldsymbol{X - Min}}{\boldsymbol{Max_{old} - Min}}(\boldsymbol{Max_{new} - Min}) + \mathbf{1} \quad (1)$$

Equation (1) converts the original rating which is 10 to 9 scale (by subtracting the minimum value from the value divided by minimum value subtracted from maximum old value, then subtract minimum scale from maximum new , add it to number 1.

STEP 4: Calculating Weighted Criteria Saw TRLs for each Entity: The next step was to calculate the TRLs value by multiplying the application of the criteria in the organization by the weight of that criteria which we calculated in (Al-Fadhli et al., 2023) and the same for data management criteria.

For the criteria of both areas Digital Transformation denoted by the letter a in equation (2), and Data Management denoted by the letter b in equation (3) using the following formulas:

$$TRL_a = \sum_1^9 NormalizedTRL \ \times Weight \quad (2)$$

$$TRL_b = \sum_1^9 NormalizedTRL \ \times Weight \quad (3)$$

Once the TRL was calculated for each area, the entities or organization can be ranked in maturity based on their weights.

Step 5: Calculate Total TRL For Each Entity: Once the TRL was calculated for each area (Digital transformation and Data management), the total TRL for each entity was calculated next as shows in equation 4 for each entity using the Geometric Mean (GM). Geometric mean used because it is more accurate than arithmetic mean in this situation

$$TRL_1 = \sqrt{TRL_a \times TRL_b} \quad (4)$$

Step6: Find Total TRL For the Government: The final step was to find the total TRL for the entire sample of government organizations using equation 5. This final TRL score represents the TRL score of AI-readiness for the government sector of Qatar:

$$Total\,TRL = \sqrt[n]{TRL_1 \times TRL_2 \times TRL_3 \times TRL_4 \times \ldots \times TRL_n} \quad (5)$$

Step 7: Validation Analysis: To measure the contribution of each independent variable (DT, DM) in the prediction of the dependent variable (TRL) we used Multiple Linear Regression analysis as per equation (6) by implementing an Ordinary Least Squares to predict the value of "Total TRL" using "DT TRL" and "DM TRL" with Python script as our tool. The Ordinary Least Squares (OLS) model is well-suited for situations where a linear relationship is assumed between the independent variables ("DT TRL" and "DM TRL") and the dependent variable ("Total TRL"). This linearity implies that any change in the independent variables is expected to result in a proportional change in the dependent variable. Additionally, OLS models stand out for their simplicity and interpretability. The coefficients obtained from OLS regression provide clear and direct insights into how each independent variable influences the dependent variable as shown in Appendix C.

Definition ii: The correlation between DT and total TRL for each entity is calculated using the correlation coefficient in equation 6:

$$\boldsymbol{r} = \frac{\sum(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum(x_i-\bar{x})^2\sum(y_i-\bar{y})^2}} \quad (6)$$

Where:

$\boldsymbol{x_i}$: variable of TRLa $\boldsymbol{y_i}$: value of Total TRL for each entity

$\bar{\boldsymbol{x}}$: mean of TRLa $\bar{\boldsymbol{y}}$: mean of Total TRL for each entity

In the same context, the correlation between DM and total TRL for each entity is calculated using the same previous correlation coefficient formula in equation 8, Where:

$\boldsymbol{r}$ is the Covariance between two standardized variables.

$\boldsymbol{x_i}$: variable of TRLb $\boldsymbol{y_i}$: value of Total TRL for each entity.

$\bar{\boldsymbol{x}}$: mean of TRLb $\bar{\boldsymbol{y}}$: mean of total TRL for each entity.

In the next step, we move on to data visualization and dashboard creation. We used Power BI for this purpose as shown in the figures discussed thoroughly in the next section of this paper along with the results analysis.

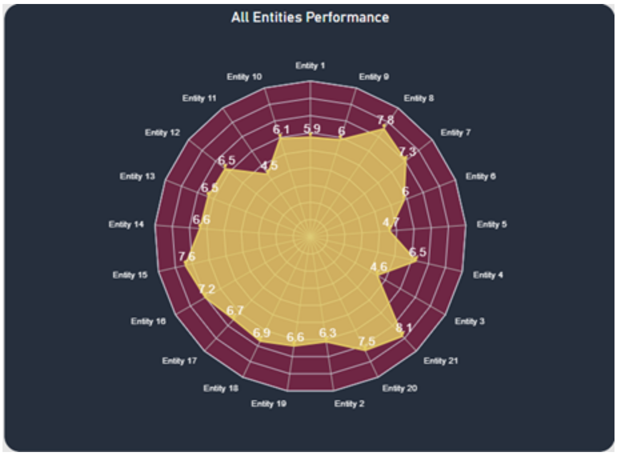
7. Results and Discussion

The research on AI readiness in government organizations in Qatar, as conducted through interviews with IT Directors, provides an accurate understanding of the state of digital transformation and data management readiness. This study contributes to the literature by applying a combination of SAW Techniques to find the weighting value for each criterion, TRLs to produce a proper assessment model tailored to measure the AI readiness of government organizations, and Multiple Regression analysis to identify the independent variable and their weights that influence in total TRL using the significance level of 5%. Qatar's AI-readiness score based on our analysis using TRLs is 6.39. When compared to its score of 5.7 in the 2023 government AI-readiness index by Oxford Insights [10], it suggests a positive trend in the country's AI readiness over time.

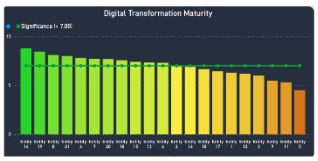
This is confirmed during the interviews with the IT Directors as many of them have mentioned technology projects related to independent variables (DT and DM), as mentioned in this study. Some of which are being pushed to the tendering process. The increase in Qatar's AI readiness score indicates positive development in the government's AI capabilities and readiness. It highlights the effectiveness of current strategies while also pointing toward areas that may require continued focus and investment. Appendix B illustrates the AI readiness index of the country.

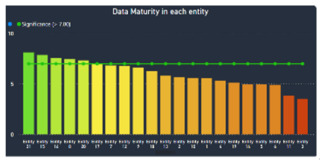
It's worth mentioning here that the results are aligned with the Oxford AI Readiness index [10] which is the most popular index in the research fields. Yet the researchers of this paper have direct access to the individuals in the study sample, and the gathered data were collected directly from the sources with the 21 government entities in Qatar leaving no room for misinterpretation of misconceptions, and it the results showed progress in the maturity of the AI Readiness criteria within the scope of research. The spiral graph using Power BI in Figure (1a) shows the distribution of entities' performance and maturity according to the Total TRL scores for each entity. Notably, entities 11, 3, and 5 are observed to have the lowest scores in their respective Total individual TRLs, with scores of 4.5, 4.6, and 4.7, respectively. These scores fall within the TRL 1-3 range (Early Stage), indicating a low level in both Digital Transformation Maturity (Figure (1b)) – characterized by initial digital capabilities and infrastructure – and Data Management (Figure 1c)), marked by basic data collection and limited integration and analysis capabilities.

This section may be divided by subheadings. It should provide a concise and precise description of the experimental results, their interpretation, as well as the experimental conclusions that can be drawn



(a) total TRL for each entity



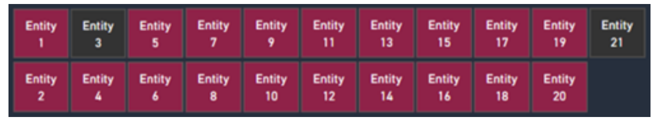


(b) DT maturity in each entity (c) DM maturity in each entity

Fig. 1: Entities Overall Performance

Delving deeper into the performance of the entities, we notice their achievements in the components of both areas (Digital Transformation and Data Management), focusing specifically on Entity 3 being the lowest-performing entity, and Entity 21 being the highest-performing entity. Our analysis reveals that Entity 3 is at a basic level or just starting the Development Stage in various criteria of Digital Transformation, including strategy and vision, innovation and services development, and experience-centric design. Furthermore, this entity demonstrates significantly low performance, firmly in the Early Stage of TRL, in crucial Data Maturity criteria like data governance and communication, data analytics and business intelligence, and data training and skill development. These criteria are identified as particularly critical for AI readiness.

Entity 21, on the other hand, stands out with its scores in both Digital Transformation Maturity and Data Management Maturity, falling within the TRL 7-9 range (advanced stage) with a TRL score of 8.1. This indicates that in the realm of Digital Transformation, Entity 21 possesses advanced digital capabilities, and fully integrated digital solutions, and demonstrates strong leadership in digital transformation. In terms of Data Management, it highlights advanced data analytics capabilities, robust data governance, and high-quality, easily accessible data. Figure 2 shows the performance comparison between the two entities. This advanced standing of Entity 21 is also evident in the high degree of advancement in data quality management, data integration and interoperability, data privacy and ethics compliance, data Training and skill development, and data access and sharing policies. Similarly, its progress is notable in various digital transformation components, including strategy and vision, innovation and services development, and experience-centric design, as well as in culture, talent and skills, and infrastructure.

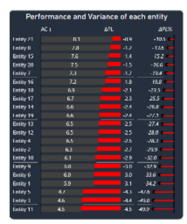


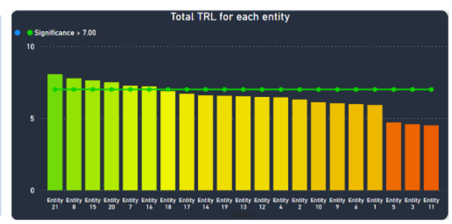
(a) Entity 3 Performance

(b) Entity 21 Performance

Fig. 2: Comparing the performance of Entities 3 and 21

Figure 3(a) displays the variance of each entity from the target score. Figure 3(b) shows that fifteen entities should work more towards the significant Score which is 7.



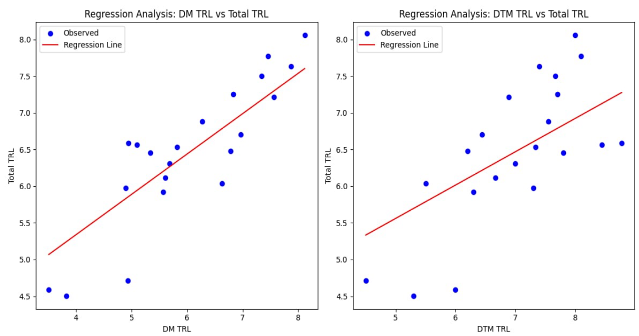


(a) Performance and Variance from the target **(b) Total TRL**

Fig. 3: Performance, Variance and Total TRL of Each Entity

The application of regression analysis, using (the OLS) model, was employed to test the coefficient of Digital Transformation Maturity (DTM TRL) and Data Management Maturity (DM TRL) scores using Python script. The model demonstrates an exceptional fit, as indicated by the R-squared value of 0.999. This indicates that 99.9% of the variability in Total TRL is accurate and effectively explained by the independent variables DTM and DM. Such a high R-squared value is indicative of strong fit of the model to the data. The coefficient for DTM TRL is 0.45 ($\hat{\beta}_1$=0.45), indicating that for each unit increase in DTM TRL, the Total TRL increases by 0.55 units ($\hat{\beta}_2$= 0.55) if DM TRL remains constant. These coefficients are statistically significant with p-values < 5%, affirming the influential role of Digital Transformation Maturity and DM TRL in predicting Total TRL. The detailed results of the Regression Analysis are included in Appendix D of this paper.

The analysis also indicates that DM values are closer to the regression line representing stronger correlation with the TRL and higher contribution to the AI Readiness Score, while the DTM values are slightly further away from the line showing less correlation and lower contribution compared to the DM values. Figure 4 shows the graphical representation of the results of the regression analysis.

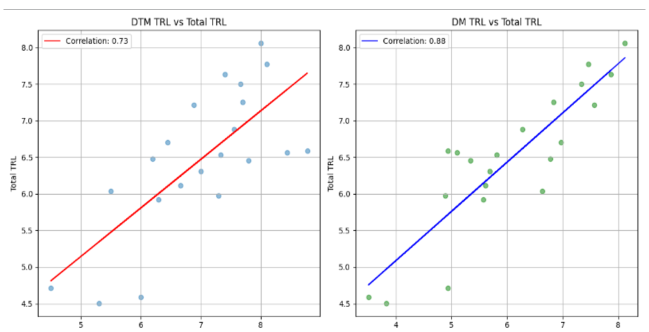


A) Regression analysis for DM and Total TRL

B) Regression analysis for DT and Total TRL

Fig. 4: Regression Analysis Results

After calculating the correlation between both areas and the TRL, the result is illustrated using Python, as shown in Figure 5. The graphs clearly illustrate that there is a very strong correlation between Data Maturity (DM) and Total TRL, with a coefficient of 0.88. Additionally, there is a strong correlation between Digital Transformation Maturity (DTM) and Total TRL, indicated by a correlation coefficient of 0.73. These two metrics significantly influence the Total TRL of government entities, although with varying degrees of impact. For a government entity aiming to improve its AI readiness, the findings advocate for prioritizing the improvement of its Data Maturity score as it is a strategic focus that will influence Total TRL, therefore, the AI Readiness of the entity



A) Correlation between DTM and Total TRL

B) Correlation between DM and Total TRL

Fig. 5: Correlation between both areas.

The 3-dimensional representation of the results illustrated in Figure 6 shows that the predicted values are remarkably close to the observed values. The x-axis represents Data Maturity (DM) measuring how advanced an organization's data management practices are. The y-axis represents Digital Transformation Maturity (DTM), which reflects how far along an organization is in implementing digital transformation initiatives and processes. The z-axis represents (Total TRL), which is a composite measure of the organization's overall readiness to adopt or implement a new technology such as AI.

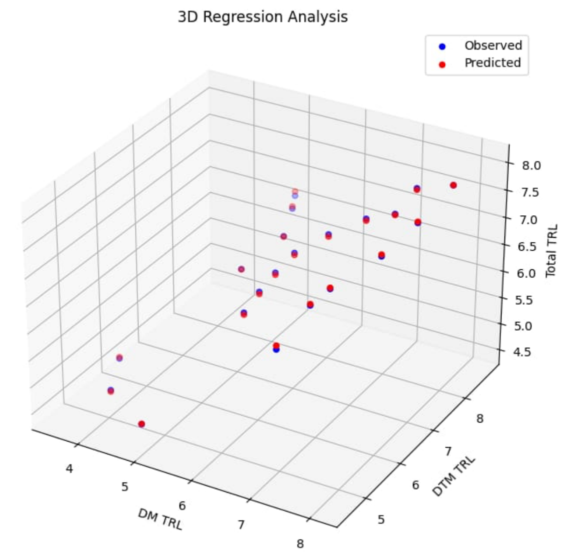


Fig. 6: 3D Regression Analysis for all criteria DT and DM

The Figure visualizes the impact of data and digital transformation maturity on an organization's AI readiness. The data points reflect the real-world state, while the predicted points reflect the model's ability to anticipate outcomes based on the input variables. Examining the spread and positioning of the blue infers how DM and DTM appear to relate to Total TRL in real-world observations.

8. Discussions

This research sets out an AI Readiness model for Government institute. This readiness is evaluated with metrics in two fundamental areas: Digital Transformation and Data Management. These metrics are used to assess the AI readiness of government institutes individually and collectively, which is a crucial step towards understanding the country's position in embracing AI technologies within the public sector. The comprehensive interviews carried out with 21 IT directors across various governmental institutes yielded a rich amount of data for the scope of the research. A combination of SAW techniques, tailored (TRLs) framework, and Multiple Linear Regression analysis using OLS model, were used to paint a detailed picture of the current state of AI readiness in Qatar indicating a modest yet positive upward trend in AI readiness. This improvement suggests that Qatar is making strides in integrating AI into government operations, although the pace of progress might be gradual.

Moreover, AI acts as a crucial catalyst for digital transformation in modern organizations, especially due to its effectiveness in decision-making when integrated with large datasets. Consequently, the implementation of AI technologies presents significant opportunities while also posing substantial challenges for organizations. Many leaders acknowledge the critical role of AI in enhancing organizational performance but are less clear on how to deploy AI to attain desired outcomes and facilitate effective digital transformation [3]. Implementing AI at a Technology Readiness Level (TRL) 9 involves merging AI technology with data produced by various processes. It also requires the cultivation of technical skills and fostering a shared understanding between the technical and business sectors within the organization [9]. This research highlights the dynamic nature of AI readiness and the need for continuous assessment and adaptation. As AI technology evolves, so must the strategies and frameworks used to assess and improve AI readiness. The study's findings provide valuable insights for policymakers, organizational leaders, and practitioners in Qatar and similar contexts. They offer a roadmap for improving AI readiness and suggest areas for future development. It is evident that while Qatar is on the right path toward AI integration in government, there is still room for growth, especially in ensuring that AI adoption is as inclusive, effective, and transformative as possible.

9. Conclusion and Future work

This research paper exposure the dynamic landscape of AI readiness and the requirement for continuous assessment and adaptation. We have offered insights into the complex interplay of AI readiness criteria based on extensive analysis and discussion with the IT Directors of Government institutes, however, this study does not delve into the broader goal of AI adoption from the state's perspective nor the specific individual institutes' circumstances. In addition, the likelihood and probabilities of risk were not in the scope of this research. This research benefited from a quantitative approach to validate the findings and further clarify the relationship between AI readiness and successful AI adoption in government sectors in the country. Moreover, the paper explores the impact of organizational context and specific AI adoption purposes on readiness factors. Finally, it could validate the component at the higher level of the government and at each government institute. As a future work, an initial step would be a quantitative research approach to examine how individual components and their combinations affect the success of AI adoption including the size the context of the organization. Such a step can overcome this limitation through two approaches: Firstly, by including participants at various levels including AI specialists, a wider range of perspectives and opinions on AI readiness can be captured. Secondly, it's recommended to delve deeper into the unique characteristics of organizations regarding AI adoption. This could be achieved through comprehensive case studies, which would also assist in distinguishing AI readiness factors based on different organizational contexts and specific AI adoption goals [4].

Results Interpretation:

- Dependent Variable: The model predicts Total TRL.
- R-squared (0.999): This value is extremely high, indicating that 99.9% of the variability in Total TRL is explained by DTM TRL and DM TRL. This suggests a very strong fit of the model to the data.
- Adjusted R-squared (0.998): This is similarly high, which confirms the model's goodness of fit even after adjusting for the number of predictors.
- F-statistic (6360): This is very high, suggesting that the overall model is statistically significant. The model is a better fit than an empty model (i.e., a model with no predictors).
- Prob (F-statistic) (<0.0001): This indicates the statistical significance of the overall regression model is extremely high.

Coefficients:

- Const (-0.0388): The y-intercept is close to zero. However, its p-value is not significant (p=0.538), indicating that the intercept is not significantly different from 0.
- DTM TRL (0.4542): For each unit increase in DTM TRL, Total TRL increases by an average of 0.4542 units, assuming DM TRL is held constant. This coefficient is statistically significant (p<0.0001).
- DM TRL (0.5502): For each unit increase in DM TRL, Total TRL increases by an average of 0.5502 units, assuming DTM TRL is held constant. This coefficient is also statistically significant (p<0.0001).

Model Diagnostics:

- Durbin-Watson (2.490): This statistic tests for autocorrelation in the residuals. A value close to 2.0 suggests little to no autocorrelation, which is the case here.
- Omnibus, Jarque-Bera (JB): These tests assess the normality of the residuals. The p-values here suggest that the residuals are reasonably well-behaved (no strong deviation from normality).

Author Contributions: Muna Alfadhli is a Ph.D. student and prepares the work, including IT director interviews, implementation models, and analysis of their output, write the paper. Prof. Sumaya Al-Maadeed is the students' supervisor; she helps with the idea, follows up on the work, and finalizes the final shape of the paper.

Funding: This research was funded by International Research Collaboration Co-Fund (IRCC) Cycle 06 (2023-2024) No. IRCC-2023-223 from Qatar University.

Data Availability Statement: We encourage all authors of articles published in MDPI journals to share their research data. All the data used came from interviews of IT directors in government sectors.

Acknowledgments: This publication was made by International Research Collaboration Co-Fund (IRCC) Cycle 06 (2023-2024) No. IRCC-2023-223 from Qatar University. The statements made herein are solely the responsibility of the authors.

Conflicts of Interest: "The authors declare no conflicts of interest."

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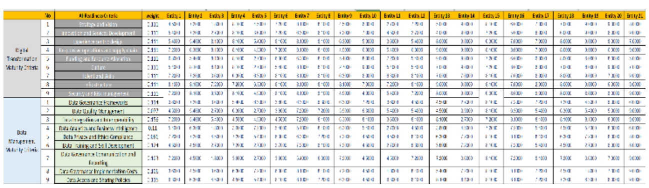
Appendix A

Table A1.1: The Collected Data in The Interviews From 21 Entities



	No	AI Readiness Criteria	weight	Entity 1	Entity 2	Entity 3	Entity 4	Entity 5	Entity 6	Entity 7	Entity 8	Entity 9	Entity 10	Entity 11	Entity 12	Entity 13	Entity 14	Entity 15	Entity 16	Entity 17	Entity 18	Entity 19	Entity 20	Entity 21
Digital Transformation Maturity Criteria	1	Strategy and Vision	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	2	Innovation and Services Development	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	3	Experience centric design	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	4	Responsive operations and supply chain	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	5	Funding and Resource Allocation	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	6	Culture	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	7	Talent and Skills	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	8	Infrastructure	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	9	Security and Risk management	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Data Management Maturity Criteria	1	Data Governance Frameworks	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	2	Data Quality Management	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	3	Data Integration and Interoperability	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	4	Data Analytics and Business Intelligence	0.11	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	5	Data Privacy and Ethics Compliance	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	6	Data Training and Skill Development	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	7	Data Governance Communication and Reporting	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	8	Data Governance Implementation Costs	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	9	Data Access and Sharing Policies	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Appendix B

The results as shown in the figure below summarize the data and visualize the Total TRL for the government sector represented by the research sample, to see from left to right the TRL index in each entity, and on the right the sum of the total TRL.

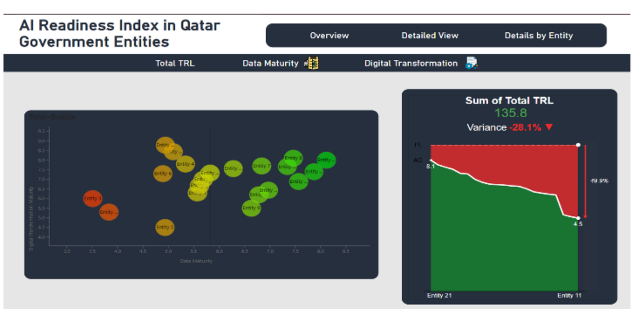
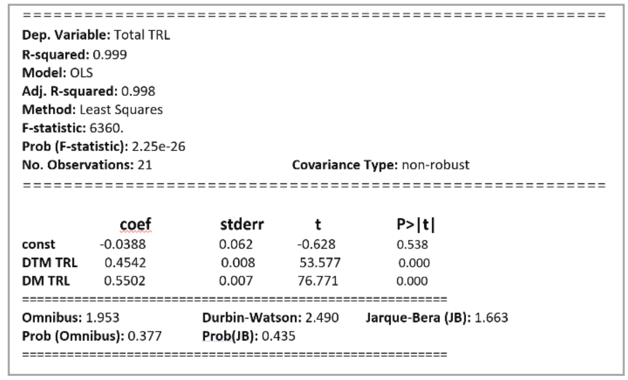


Figure B.1 AI Readiness in Qatar

Appendix C



```
=====================================================================
Dep. Variable: Total TRL
R-squared: 0.999
Model: OLS
Adj. R-squared: 0.998
Method: Least Squares
F-statistic: 6360.
Prob (F-statistic): 2.25e-26
No. Observations: 21                      Covariance Type: non-robust
=====================================================================
            coef       stderr      t          P>|t|
const      -0.0388     0.062      -0.628      0.538
DTM TRL     0.4542     0.008      53.577      0.000
DM TRL      0.5502     0.007      76.771      0.000
=====================================================================
Omnibus: 1.953            Durbin-Watson: 2.490     Jarque-Bera (JB): 1.663
Prob (Omnibus): 0.377     Prob(JB): 0.435
=====================================================================
```

Figure C.1 Regression Analysis Results