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Towards the governance of government data using artificial intelligence

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Abstract: Governance using artificial intelligence begins with data governance which is certainly not a new concept. That is, when data is collected, organizations need a certain policy level and insight to govern their data management. To a large extent, data policy has remained background in nature, although data-driven businesses usually require data governance to be of prime concern. However, in the past few years, in the face of the twenty-first century challenges of changing events, data governance has been at the forefront of discussions regarding almost everything in the media and the boards of various organizations that are taking the first steps towards their AI. In addition, the recent increase in government participation in data privacy is playing a prominent role in this development. His main focus was on the risks of artificial intelligence and the maintenance of its framework in the face of rapid machine learning development. This has contributed to the various institutions and companies starting to verify that data governance has not established an investigation in a way that leads to trading the massive shift towards the demanding machine in the current era of artificial intelligence. As with artificial intelligence we bring the new governance requirements related to artificial intelligence that require a proper framework that is applied transparently. Currently, with the spread of data science and tools that put data across the facility and become available to the many and not only to the elite few (such as data scientists, or even analysts). Explain that companies are using more data in many ways than in the past, and this represents a great value for companies, as in fact, they have witnessed great success in using data, which led to business adoption of this approach. However, this may also present new challenges for these Firms that business IT companies unable to handle data requests create a power struggle between two trends that slows the overall progress of AI in the facility. This has also led to a fundamental shift and organizational change in the type of data governance that data can be used, while It also protects data from risk, which is an answer to this topic. With this in mind, this work explores how many companies participate in defining the scope of AI. It is needed in order to strengthen its governance approach. With data governance as a basis for this, while it may require an organizational change to verify it in the long run, which may allow the organization's AI to become in the scope in which it is responsible and sustainable, this work details the framework of the AI work governance framework that it intends to adopt by the various institutions.

Keyword: Governance, artificial intelligence, organizational, data, government.

Introduction

The concept of AI governance and its need

Traditionally, data governance includes policies, roles, standards and measures to improve the use of information that enables an organization to consistently achieve its business goals and objectives(Janssen et al., 2020). Data governance also emphasizes the quality and security of the organization's data through a clear explanation of who is responsible for any data, in addition to determining the actions that can be taken using various appropriate methods. With the emergence of data science, machine learning, and artificial intelligence, opportunities have become available to expand the huge amounts of data that contributed In the emergence of the information revolution that became apparent on the actions of companies.(Winter & Davidson, 2019) The significance of this development is that the existing data governance strategies have become sufficient to sustain the increased governance activity(Lam et al., 2021). As it became possible for data scientists and analysts to obtain data at a high speed, in addition to being able to argue about the needs of businesses from different and varied huge data at a high speed. It also provided the opportunity to adopt government interests in countries of the world in urgent need of greater data than it was before, and at the same time many organizations around the world are making more decisions with more large data as well.(Bennett, 2017) Various institutions and companies have noticed the importance of effective governance and quality control required for analysts, data scientists, decision makers and business users in order to deal with the dimensions of governance in a repetitive

manner and in ways that may not be consistent with each other. This can lead to a complete lack of trust in each stage of the data flow, and when the people interacting with the organization do not trust the data you provide, they cannot make the right decisions with the confidence possible. Historically, IT companies have addressed data governance and are ultimately responsible for it. But with the business dynamism of the data age, which has become available to everyone, as supervision, access and ownership of data have become business questions and that IT teams and those who are placed in positions of responsibility for separate parts of data governance in a way that may be incorrect are available in the performance of various business methods. The reason for this may be, that a set of skills required for all components of governance is challenging, besides that those responsible for data governance will have expertise related to data engineering, privacy, integration and, modelling. Also, everyone who works in the field of data governance must have experience in all of the following: What is data? Where does the data come from for the data? How and why data is valuable to the business? How can data be used in multiple businesses? How data is finally used, which in turn is responsible for the AI strategy, in short, data management requires the collaboration of all IT users at the same time (Kovacova et al., 2019). Thus, the traditional data governance program oversees a set of activities that include data security, references and master data management, data architecture, data quality, and data specifications management, which is illustrated in the following figure (1.1), which shows the extent of the difference between data governance and artificial intelligence governance(Medhora et al., 2018).

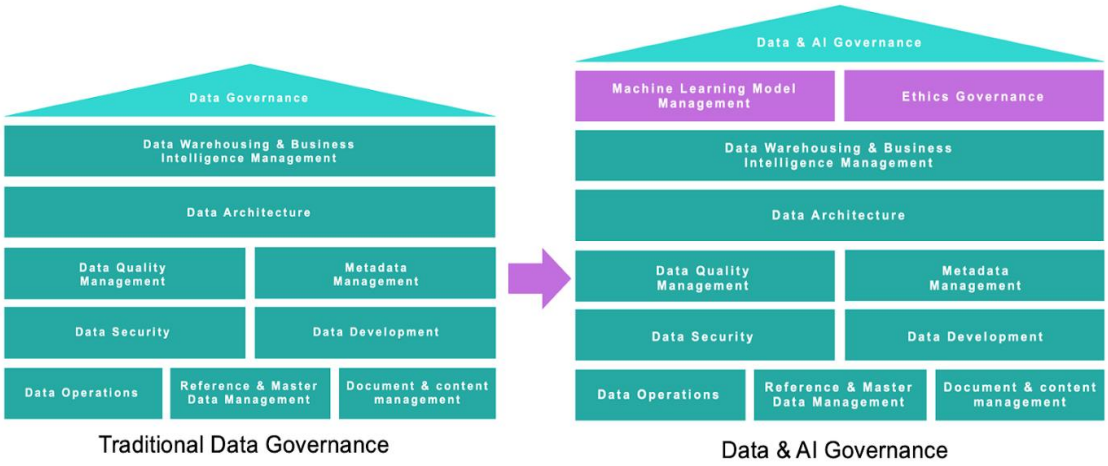

Figure (1.1) difference between data governance and artificial intelligence governance

Governance to using AI

Most businesses now know data governance as a very important part of their data strategy. (Reddy et al., 2020) more so, often than not, that's because bad data governance is often risky. This is not a cause to prioritize them, but after all compliance with system, avoidance of bad actors, or security concerns are all critical to organizations that must take appropriate measures to address them(Schneider et al., 2020). In any case, governance programs are not just utilitarian programs because they make the company sound, and their effects are more extensive than that, as they contribute to achieving the following:

1. Saving money: Organizations believe that poor data quality is responsible for the loss of a lot of money and also the cost of security breaches is very huge and the governance of data power as well as data quality and security leads to vast savings for the company.
2. Improving trust: When governance is implemented in an appropriate manner, it can improve trust in data at all levels of the organization, allowing workers to be more confident in the decisions taken and improving confidence in the analysis and models produced by data scientists in addition to the accuracy of the data resulting from improved data quality.
3. Reducing Risk: Governance programs reduce the risks of negativity associated with data breaches and misuse of data while increasing regulations related to data. Governance is not limited to maintaining the company's integrity, data management and artificial intelligence components to raise the company's level to

high quality standards, and transforming data and artificial intelligence systems into essential components in institutions.

Machine Learning Framework Model Management and AI Governance:

- Management of the Machine Learning Governance Framework Model

Once the data governed by the data governance software is used, the development and use of the Machine Learning Framework model in production requires clear and unambiguous policies, roles, standards and measures(Barai et al., 2015). The robust machine learning management framework model program aims to answer the following questions: Who is responsible for the performance and maintenance of machine learning models and How machine learning models update and/or reconfigure their model's computation What performance measures are measured when the model is developed and selected, and what is the acceptable level of business performance? How do models monitor over time to spot any shortcomings, unexpected data, and anomalies? How do you monitor models and can they be explained to those outside the development team? It is worth noting that the management of the machine learning framework model will play an important role in AI strategies. In current realities and beyond, such as the impact of project artificial intelligence in developing systems to keep pace with future economic change(Piano, 2020).

- Responsible AI Governance

The second new aspect of the contemporary governance strategy is the oversight and policies related to responsible AI. While this is certainly the focus of media attention, along with public debate and controversy, the somewhat responsible AI has also been overlooked at the same time that it has to be incorporated as a tangible part of the governance programme. Which is referred to as a science, 'data science', and it is likely that because there is a realization among some that AI is intrinsically objective, and that its recommendations, predictions, or any output from a machine learning model is not subject to the biases of individuals.(Reddy et al., 2020; Tan & Taeihagh, 2020) When this is the case, the question of responsibility will not match AI where the algorithm will simply be an indubitable representation of reality. This concept is contradictory, not only because the misunderstanding that weakens the collective and individual responsibility towards the responsible AI aims to address this misconception and answer the questions as follows: What data is chosen to train the models, and does this data contain prior biased data in it What are the protected characteristics that should be omitted from the model training process, such as gender, age, religion, and ethnicity How bias is calculated and mitigated in the model How is the privacy of a customer, employee, user, and citizen data respected How long can the data be kept legally after its original use Are collection methods aligned And our warehousing is not only with regulatory standards but also with organization-specific standards

Successful Data Governance Strategies Five governing keys can be distinguished to explain a successful AI governance strategy as follows:

1. Top-down and bottom-up strategy: Even an AI governance program requirements to be nurtured and supported by the top management of an organization. Without the support and leadership of the organization, it does not appear to be making the right changes that define complete transparency. Expected changes are often challenging to improve data security, quality, and management. At the same time, individual teams must take collective responsibility for the data that is managed and analyzed for production.(Spremic, 2017) There are needs associated with a culture of continuous improvement, and issues of data ownership, which is a bottom-up approach achieved along with top-down communication and recognition of teams that have made real improvements that can serve as an example for other organizations.
2. Balance between governance and empowerment: Governance should not hinder or inhibit creativity, and instead should enable and support creativity. In many cases, this means that teams need to distinguish between proof-of-concept initiatives, self-service data initiatives, and industrial data products as well as the governance needs surrounding each.(Kuziemski & Misuraca, 2020) There should be space for exploration and experimentation, but teams need to make a clear decision about when they should fund self-service projects, or fund proof of concept, testing and confirmation of concepts to become a viable solution.
3. Core Quality: In a lot of companies, data products created by data science and business intelligence teams do not have the same commitment to quality as traditional software development (through movements such as programming and literal or craft).(Castro et al., 2021) There are many ways to do this that have arisen since the enthusiasm ten years ago, when data science was still a relatively new field, and practitioners,

They work in experimental environments that do not pay for the proper product. While data science is used in developed countries, its application and importance is largely within the framework of quality standards applied to developing software that needs to be re-applied. The quality of the data itself is more important to many than ever, but products also need to include the same high quality standards through coding review, testing, and continuous integration or continuous development that software does when the visions are trusted and implemented in business.

4. Model Management: As machine learning and deep learning models become more prevalent in decisions made across industries, model management becomes a key factor in any AI governance strategy. This is especially true as the economic climate has shifted, causing massive changes to basic data and models that permeate and drift more rapidly. It also needs continuous monitoring, model refresh, and testing to ensure that models are performing following business needs.(Castro et al., 2021; Lima & Delen, 2020) To this end, learning operations attempt to take the best from MLOps and machine development processes from software development and apply them to data science. DevOps MLOps The following figure (2.2) shows the dimensions of machine learning operations

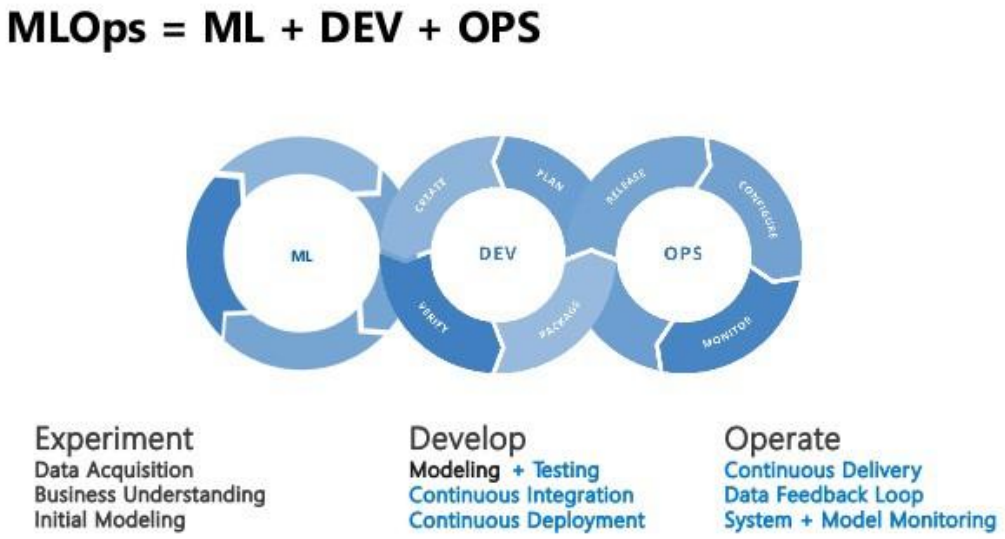

Figure (2.2) machine learning operations

Transparency and Responsible AI: Under the component, data scientists write code and adhere to high quality standards, yet still endow a certain level of oversight to complex algorithms. In other words, it's not just the quality of the data or the coding but the assurance that the models do what they were meant to do. There is increasing scrutiny of decision-making by machine learning models, as models make decisions that affect the lives of many people every day. On this, you understand the effects of the decisions that are made and make models explaining them that are essential to the people affected and the companies that result from them.

Data Operations in AI Governance Framework:

- Data and Artificial Intelligence Governance:

As mentioned in the abstract of this work, data and artificial intelligence governance are not easy, as their programs require consistency and functional change, and both of them become a challenge in larger organizations.(Brous & Janssen, 2015; Dwivedi et al., 2017; Janssen et al., 2020) More than that, the success of AI governance is a question, not just success processes, and it affects both people and technology as able-bodied Also, despite the obvious importance and tangible usefulness of an effective AI governance program, there are many pitfalls in that governance be able to be affected and fall along the way, which may impede the efforts made by people due to the lack of the following:

- Lack of leadership care:

where The program of governance without the care of the leaders of the organization, which is represented in policies without actual implementation of them. (Brous & Janssen, 2015; Janssen et al., 2020) Data scientists, analysts, and business people often explain the current status quo when there is no top-down governance policy that is recognized by the leadership when taking positive steps needed to improve data governance culture When there is no intellectual property culture and commitment to improving the use and exploration of data available throughout the organization, this makes it difficult for a data governance strategy to be effective It is noted that the answer to this is often due to the extent of the leaders' care as well as the availability of communication and the tools needed for them.

- Operations:

The AI governance processes in the organization are affected by the following factors: Weak communication lack of clear communication around data governance policies, roles, standards, and measures can lead to an ineffective data governance program and if workers are not familiar with or Educated about what the required policies and standards should be they can then do what is best for their organization Lack of training and education resources Both training and education are very important parts of good data and AI governance. As this not only confirms that everyone is familiar with the policies, but it also cannot help explain why governance is particularly important to the organization. In this context, training and education resources such as web-based meetings, e-learning, on-line documentation, e-mail, video, etc. that illustrate the dimensions of introductory and continuing education for employees are considered.

- Technology:

Lack of a central repository: The central controlled environment through which all information collection is implemented or occurs in a central data repository that contributes to making data and artificial intelligence governance in the simplest terms. Data science, machine learning and artificial intelligence platforms may also be environment biased, which must include basic features such as providing minimal contextual documentation, clear project delineation, task organization, change management, backtracking, monitoring, and organization-wide security.

AI Governance Model Framework:

The AI Governance Model Framework includes guidance for measures that support the responsible use of AI to be applied by organizations in various fields as follows:

1. Internal governance structures and measures: Which is the measure taken for governance within government institutions and knowledge of the risks and responsibilities that may affect the decision-making processes of organizations and institutions
2. definition the AI decision-making model : This is an important stage for institutions and organizations to know the extent to which artificial intelligence risks are tolerated and the extent to which it is acceptable to confront those risks and to take the appropriate decision to implement artificial intelligence in the process of institutions and organizations.
3. Operations Management: Management processes are an important stage to consider when developing artificial intelligence models, which in turn are data management, testing, and maintenance..
4. Customer Relationship Management: It describes the strategies used to communicate the elements of conformity to customers, and is a representation of how the framework model is implemented by the organization. All of this represents internal governance structures and measures that verify that organizations must include internal governance structures and measures which in turn serve as a strong oversight of the organization's use of artificial intelligence.

Organization's Internal Governance Structures

When necessary, existing governance mechanisms and good structures can be used. The hazards connected with artificial intelligence, for example, can be controlled through an enterprise risk management system that can be integrated into the organization's assessment and management through an ethics review board or similar structures.(Gasser & Almeida, 2017; Wirtz et al., 2019) Additionally, organizations must choose whether components of their internal governance frameworks are suitable. Decentralization, for example, can be careful to include ethical issues in everyday decision-making at an early stage when relying exclusively on a centralized governance process that may not be appropriate for an When necessary, at the operational level The

sponsorship, support, and governance of artificial intelligence for the company, as well as the sponsorship, support, and support of senior management and the board of directors, are crucial and necessary for the organization that adopts it. Apart from that, businesses should incorporate some or all of the following elements into their internal governance structure:

1. Know the responsibilities involved in spreading the ethics of artificial intelligence
2. Maintain, monitor and review the published AI models to take improvement actions when needed.
3. The work of reviewing the communication channels and interactions of consumers and customers in order to make a review of it.
4. Confirmation of the corresponding workforce that deals with artificial intelligence systems and is trained to interpret the outputs or decisions of the artificial intelligence model used.

To achieve a specific purpose estimate and manage risks of imprecision and bias**,** in addition to review exceptions identified throughout the training model.

- There are no processes for an unbiased data set, so organizations must strive to understand the ways of bias in data units and address this in safety measures and deploy strategies related to AI.
- Monitoring and information systems, as well as processes that ensure the safety and suitability of a specific administrative level, as well as knowledge of other challenges associated to broad artificial intelligence It is feasible to construct AI systems that stress the amount of confidence of the predictions contained, in addition to outlining the possible elements of focusing on why the AI model included a given level of confidence rather than why the prediction succeeded. Ensure appropriate information transfer wherever there are changes in key individuals involved in AI performance.
- Reviewing internal governance structures and process when there are fundamental change to organizational structures or to key individuals concerned in the activities.
- Reviewing internal governance structures and measures periodically to guarantee their conformity and efficiency.

Artificial intelligence decision-making model:
When deciding on this model, the following should be noted:

1. Organizations should decide on the goals of employing commercial AI before accepting the implementation of AI solutions. For example, guaranteeing consistency in decision-making, improving operational efficiency, lowering costs, or providing new product features that provide consumers more options. That is companies that make decisions and analyze risks associated with AI within the context of institutional principles that reflect the community norms of the communities in which they operate..
2. Organizations operating in several nations must be as aware of regional differences in social norms as possible Individuals' risks associated with recommendation engines for e-commerce items and services, or the acceptance mechanism of apps available by default for online travel and travel insurance may be lower than those associated with algorithmic trading facilities available to investors.
3. Some of the risks to which individuals may be exposed may only be seen at the group level. For example, when a big number of people make identical judgments at the same time, the use of a widely used recommendation algorithm may create a shift in behaviour and an increase in market volatility in general. There are additional types of hazards that may be known in addition to the dangers that individuals may be exposed to, such as those connected to the organization's commercial reputation.
4. Organizations determine and weigh their business objectives in light of the risks of artificial intelligence that they must face through their institutional values, where those organizations can estimate whether the targeted AI deployment and the chosen model for algorithmic decision-making are reliable with their values axis, that is, the lack of compatibility and .
5. Organizations must identify and review potential or potential risks compatible with technological solutions continuously while mitigating these risks, and maintain a response plan when mitigation fails, using an iterative and continuous process that includes the definition of business objectives, risk, and the selection of an appropriate decision-making model. This procedure has been documented. By periodically analyzing the assessment's impact to aid the organization in establishing clarity and confidence in the employment of artificial intelligence solutions, as well as assisting the company in responding to fundamental changes made by individuals and other organizations.

The AI model framework, which builds on the prior approach to risk management, defines three main models of decision-making with varying degrees of human oversight over the process that become obvious over time..(Barry & Doskey, 2020; Loftus et al., 2020) Data proportions can be visualized to show how data goes along its journey, interacts with other data, and changes in views. In this situation, we can infer three different sorts of data ratios

- Attributing the data to the back that look at the data through its final use and the extent of its date of origin,
- Data forward ratios that start at the data source and follow through their end use.
- Data ratios from one party to another that consider the whole solution from the source to the ultimate usage and vice versa. An organization can determine the quality of data based on the following changes, track potential sources of mistakes, update data, and attribute data to its multiple sources by keeping a data source record. In some circumstances, and when the data source is different in terms of building the chosen model, the AI governance model framework understands all of this. Data units can be collected from a trusted third party that can combine data from many sources.

Algorithm and AI governance model:

Different business organizations should believe in the actions required to improve the clarity of the algorithms used in AI governance models by understanding how they work and how they arrive at a certain forecast that can be communicated. (Lim & Taeihagh, 2019; Taeihagh, 2021) The goal of this skill is to explain AI predictions in order to foster empathy and trust in AI applications. To demonstrate accountability to individuals and/or legislators, organizations that deploy AI solutions should include descriptions of AI solution design and typical behaviour in a product or service explanation, as well as documentation of technical specifications linked to the specific system. This could entail identifying certain characteristics, features, or models that have been chosen above others.(Al-Ma'aitah, 2019) The firms that use them must bring in any requests for assistance from AI solution providers because they are in a better position to explain how to use the solutions they provide. The AI model framework specifies what can be accomplished by describing the function of AI algorithms and/or how it incorporates predictions into the required decision-making process. Depending on the technological competence of the intended beneficiaries, the organizations that implement the AI model structure may provide varying levels of information in their explanations (for example, individuals, businesses, or other organizations and legislators). The AI model, for example, could have an impact on the mathematical model. To construct a smart system in this setting, a training and testing model is required (a system that includes artificial intelligence technologies) (Taeihagh & Lim, 2019) Organizations that use smart systems should keep track of how the training and selection model variables and processes are carried out, as well as the justifications for any judgments made and the risk mitigation mechanisms in place. In this context, the field of machine learning aims to localize the mechanism of the iterative search process for the best-applied model.(Lim & Taeihagh, 2019) Organizations that use high-quality algorithms and selected sub-models are thought to be capable of achieving AI governance and conduct goals. In the event that audits of algorithms are required, it should be emphasized that technical explanations may not always be knowledgeable and specific. Explanations of the functionality of implicit AI algorithms may be more useful to non-specialists than explicit model descriptions. Avoiding things that are unreal and unreal, for example, is the type of powerful explanation that businesses should consider. May process or be accountable for delivering algorithm-related information, such as personal information, intellectual property, money laundering detection, information security, fraud or corruption prevention, or algorithm evaluation, where precise information is necessary. or algorithmic decisions that may mistakenly reveal secret company information and/or enable unscrupulous actors to avoid exposure. Even though frequent documents do not substitute thorough feedback, companies may investigate scoring repeated findings using an AI model. Repetition refers to the ability to carry out an action or decision according to the same scenario in use. Where you can deliver performance to AI users with some confidence

Client Relationship Management using AI

Appropriate communication establishes and maintains open relationships between organizations and individuals (including workers), which encourages trust(Wang et al., 2020). When using AI, organizations must consider the following criteria to successfully implement and manage their communications initiatives.

1. Public disclosure: Companies must make general information regarding the use of artificial intelligence in their products and/or services available to the public. This could contain details on how artificial

intelligence is employed in making specific judgments, as well as the role artificial intelligence plays in the decision-making process.(Aljawarneh & Al-Omari, 2018) Companies categorised to manufacture a navigation system Identification that users must know that GPS artificial intelligence was used to build various routes from point (A) to point (B), for example, that is, how the user of the navigation system decides which of the available techniques to employ, and the portal available on the line It may tell its users that the Portal interacts with powerful AI Chabot

2. Increased Transparency: By enhancing openness in interpersonal relationships, increased transparency enhances confidence and acceptance of AI Mile. Organizations must consider explaining how AI affects people in order to do so, especially when the choice is overturned. For example, an organization may inform individuals that their credit rating causes them to be denied credit not only by the organization but also by other similar organizations, but that this decision is overturned if individuals can provide more evidence and proof of the requested credit's usefulness.
3. Use understandable communication language to increase transparency: In this context, there are multiple tools and measures to facilitate readability. There are also higher impact decisions delivered in an easy-to-understand manner with the need for transparency about the technology used.
4. Availability of ethical standards: Ethical standards govern our development Artificial intelligence and its use It is imperative that organizations are able to perform ethical assessments and prepare summaries of these assessments that are highly understandable
5. Policy to explain: Organizations should develop a policy of explanations and explanations provided to individuals, including explanations of how AI works in the context of the decision-making process, how a specific decision was made, the reasons behind the decision, and the impact and effects of the decision, and information about a specific decision may also be available upon request.
6. Human AI Interaction Review: Organizations should test the user interface with regard to addressing usability and usability issues before use process so that the user interface serves its future objectives.
7. Withdrawal options: Organizations should carefully consider when they decide to offer the option to opt out, as well as whether this option is offered by default or upon request, based on factors such as the degree of risk damage to individuals, the reversibility of the damage necessitating actual commitment, and the availability of alternative decision-making mechanisms, among others..
8. Providing communication channels to customers: The following are two types of communication channels that must be provided to customers: Feedback channel that is used to raise feedback or raise questions related to individuals. This channel is managed by an organization's data protection specialist when appropriate.

Individuals may discover flaws in personal data used in decisions that impact them as a result of this, and this data may also allow individuals to rectify their own data. The Quality Service Manager, who is one of the most important people in these stages, is in charge of this correction and feedback, which helps to maintain the data's authenticity. And there is a decision review channel that is separate from assessing current commitments for anyone who want to provide input and question the physical inferences that operate on the data. Individuals can request a review of AI decisions that affect them through organizations..(Goldstein et al., 2012) The choice is made entirely by computer. Individual review of the request by a human agent is required, and if the decision impacts the individual, the effect must be material. That does not distinguish it from artificial intelligence(Tan & Taeihagh, 2020) This necessitates a partial system with prior review to confirm the conclusion offered in order for the human aspect to truly examine the decision, which is not different from AI

Conclusions:

Data governance in general, and all aspects of it, are still important, whether it's for data superiority, master data management, or data security. Data science, machine learning, and artificial intelligence have all expanded the scope and applicability of data governance. Various organizations require intimacy, investment, culture, and the correct communications to ensure that the data and AI governance program is effective and delivers changes across the firm. The framework for the AI governance model is not complete or comprehensive, but rather an open document for feedback. As AI technologies evolve, ethical issues and governance issues develop as well.

Reference

[1]. Al-Ma'aitah, M. (2019). Drivers of E-Government Citizen Satisfaction and Adoption: The Case of Jordan. *International Journal of E-Business Research (IJEBR)*, *15*(4), 40–55.
[2]. Aljawarneh, N., & Al-Omari, Z. (2018). The role of enterprise resource planning systems ERP in improving customer relationship management CRM: An empirical study of safeway company of Jordan. *International Journal of Business and Management*, *13*(8), 86–100.
[3]. Barai, G. R., Krishnan, S., & Venkatesh, B. (2015). Smart metering and functionalities of smart meters in smart grid-a review. *2015 IEEE Electrical Power and Energy Conference (EPEC)*, 138–145.
[4]. Barry, P. S., & Doskey, S. (2020). Utilizing Artificial Intelligence to Make Systems Engineering More Human. *A Framework of Human Systems Engineering: Applications and Case Studies*, 19–41.
[5]. Bennett, S. (2017). What is information governance and how does it differ from data governance? *Governance Directions*, *69*(8), 462–467.
[6]. Brous, P., & Janssen, M. (2015). Advancing e-Government using the internet of things: a systematic review of benefits. *International Conference on Electronic Government*, 156–169.
[7]. Castro, A., Villagrá, V. A., García, P., Rivera, D., & Toledo, D. (2021). An Ontological-Based Model to Data Governance for Big Data. *IEEE Access*, *9*, 109943–109959.
[8]. Dwivedi, Y. K., Rana, N. P., Janssen, M., Lal, B., Williams, M. D., & Clement, M. (2017). An empirical validation of a unified model of electronic government adoption (UMEGA). *Government Information Quarterly*, *34*(2), 211–230.
[9]. Gasser, U., & Almeida, V. A. F. (2017). A layered model for AI governance. *IEEE Internet Computing*, *21*(6), 58–62.
[10]. Goldstein, K. M., Minges, M., & Surya, P. (2012). Making government mobile. *Maximizing Mobiles*, 87–101.
[11]. Janssen, M., Brous, P., Estevez, E., Barbosa, L. S., & Janowski, T. (2020). Data governance: Organizing data for trustworthy Artificial Intelligence. *Government Information Quarterly*, *37*(3), 101493.
[12]. Kovacova, M., Kliestik, T., Pera, A., Grecu, I., & Grecu, G. (2019). Big data governance of automated algorithmic decision-making processes. *Review of Contemporary Philosophy*, *18*, 126–132.
[13]. Kuziemski, M., & Misuraca, G. (2020). AI governance in the public sector: Three tales from the frontiers of automated decision-making in democratic settings. *Telecommunications Policy*, *44*(6), 101976.
[14]. Lam, K., Iqbal, F. M., Purkayastha, S., & Kinross, J. M. (2021). Investigating the Ethical and Data Governance Issues of Artificial Intelligence in Surgery: Protocol for a Delphi Study. *JMIR Research Protocols*, *10*(2), e26552.
[15]. Lim, H. S. M., & Taeihagh, A. (2019). Algorithmic decision-making in AVs: Understanding ethical and technical concerns for smart cities. *Sustainability*, *11*(20), 5791.
[16]. Lima, M. S. M., & Delen, D. (2020). Predicting and explaining corruption across countries: A machine learning approach. *Government Information Quarterly*, *37*(1), 101407.
[17]. Loftus, T. J., Tighe, P. J., Filiberto, A. C., Efron, P. A., Brakenridge, S. C., Mohr, A. M., Rashidi, P., Upchurch, G. R., & Bihorac, A. (2020). Artificial intelligence and surgical decision-making. *JAMA Surgery*, *155*(2), 148–158.
[18]. Medhora, R. P., Aaronson, S. A., Aggarwal, S., Breznitz, D., Ciuriak, D., Clement, A., Doidge, N., Geist, M., Haggart, B., & Katz, A. (2018). Data Governance in the Digital Age. *Data Governance in the Digital Age*.
[19]. Piano, S. Lo. (2020). Ethical principles in machine learning and artificial intelligence: cases from the field and possible ways forward. *Humanities and Social Sciences Communications*, *7*(1), 1–7.
[20]. Reddy, S., Allan, S., Coghlan, S., & Cooper, P. (2020). A governance model for the application of AI in health care. *Journal of the American Medical Informatics Association*, *27*(3), 491–497.
[21]. Schneider, J., Abraham, R., & Meske, C. (2020). AI Governance for Businesses. *ArXiv Preprint ArXiv:2011.10672*.
[22]. Spremic, M. (2017). Governing digital technology–how mature IT governance can help in digital transformation? *International Journal of Economics and Management Systems*, *2*.
[23]. Taeihagh, A. (2021). Governance of artificial intelligence. *Policy and Society*, 1–21.
[24]. Taeihagh, A., & Lim, H. S. M. (2019). Governing autonomous vehicles: emerging responses for safety, liability, privacy, cybersecurity, and industry risks. *Transport Reviews*, *39*(1), 103–128.
[25]. Tan, S. Y., & Taeihagh, A. (2020). Governing the adoption of robotics and autonomous systems in long-term care in Singapore. *Policy and Society*, 1–21.

[26]. Wang, X.-L., Lei, N., & Hou, Y.-Z. (2020). How does human resource department's client relationship management affect sustainable enterprise performance-in the context of artificial intelligence? *International Journal of Technology Management*, *84*(1–2), 50–69.

[27]. Winter, J. S., & Davidson, E. (2019). Governance of artificial intelligence and personal health information. *Digital Policy, Regulation and Governance*.

[28]. Wirtz, B. W., Weyerer, J. C., & Geyer, C. (2019). Artificial intelligence and the public sector—applications and challenges. *International Journal of Public Administration*, *42*(7), 596–615.