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# Chapter 6: Governance Models for Responsible and Controlled AI Systems

## 6.1. Introduction

Amid growing societal concerns about artificial intelligence (AI) systems' potential negative effects and the need to ensure that AI systems are built and used responsibly, several principles for responsible artificial intelligence (AI) and machine learning have emerged and expanded across industry, academia, civil society, and governments. Central in these discussions is the need for appropriate governance mechanisms to ensure that AI technologies are not only developed but also used in responsible ways. Governance encompasses a multitude of aspects, from establishing legal frameworks that impose requirements covering the entire development life cycle of an AI system to the strategic and operational decisions made to execute projects for AI systems. The AI-SMP concludes three major areas of governance: (a) objectives that define outcomes, (b) control and assurance mechanisms that ensure those outcomes are achieved, and (c) privacy and data governance.

Definitional differences among AI systems can lead to very different governance requirements and objectives. This is illustrated in the analysis of the necessary requirements and controls for general AI systems versus very narrow AI systems that provide targeted solutions to highly constrained specific problems. Such systems are usually not responsible for their actions and decisions, but their responses still need to be controlled. General-purpose models introduce much greater uncertainty because their potential set of responses and actions is massive, seldom completely controllable, and therefore extremely difficult to audit. General systems capable of producing human-level quality in natural language generation, understanding, and translation have been deployed commercially under the "beta" concentration sign, with developers warning users about potential harms, biases, and reliability issues.

### 6.1.1. Overview of Responsible AI Principles and Scope

The outcome of Artificial Intelligence (AI) systems depends not only on the inherent complexity of their components and the multiplicity of the datasets but also on the processes that guide the development, deployment, and use activities. The notion of Responsible AI is an objective-based framework that advocates for the incorporation of Ethical Principles during all the life-cycle stages of AI systems. It specifies a set of ethical frameworks, Trust, Transparency and Accountability which act as foundational stones, the Essential Governance Objectives, the Internal and External Stakeholders associated with these objectives and proposes suitable Governance Models that form the basis for Control and Assurance Mechanisms.

Further, it aims to mitigate the intricate risks ascribed to all AI systems, especially those involving High-Risk AI Systems as defined by the EU AI Act. Two important risk categories are explored in detail: the implications related to data, mainly Data Quality and Bias, and those concerning Privacy. Nevertheless, there is still a vast territory of theoretical and application knowledge related to Responsible AI that needs stimulating and must capture the attention of scientists and researchers, as well as developers and industry. It should build bridges across different cultures, traditions and knowledge areas that can know how to ensure Responsible AI to be a shared ambition of human life and a contribution to the achievement of the United Nations Sustainable Development Goals.

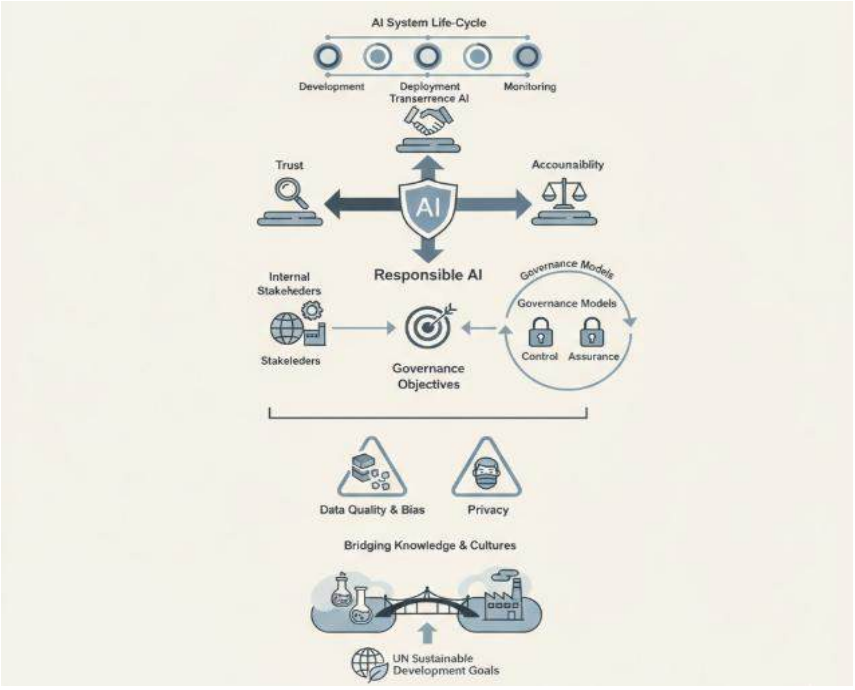


**Fig 6.1:** Operationalizing Responsible AI: A Multi-Stakeholder Governance Framework for Life-Cycle Integrity, Risk Mitigation, and Global Sustainability

## 6.2. Foundations of Responsible AI

The ethical frameworks and normative principles outlined in the OECD Recommendation on AI provide a strong foundation for the governance of AI systems. However, ethically responsible AI systems are not necessarily trustworthy, and trust, transparency, and accountability are essential for trust-building. Consequently, the principles of trustworthy AI should be explicitly integrated into responsible AI analyses and frameworks. Trust refers both to the behaviour of the AI system and to the behaviour of the actors who design, develop, deploy, and utilise these systems. Users must have sufficient information about the AI system in order to build trust in it, while the designers must assume responsibility for the behaviour of the systems that they create.

AI control is a broad concept encompassing various mechanisms designed to ensure and enhance the safety, reliability, and robustness of AI systems. Sufficient control mechanisms and assurance frameworks facilitate the deployment and introduction of AI systems with an explainable operation mechanism. Concrete policy instruments and technical control mechanisms are the primary drivers of AI system control. Since responsible AI governance thus entails the introduction of effective control measures for those AI systems with a high expected societal risk, the concept should be used in connection with such systems. As explained in the following sections, this aspect of governance is particularly relevant for centralised governance models.

### 6.2.1. Ethical frameworks and normative principles

Various ethical frameworks can inform the processes, objectives, and policies for the responsible development and deployment of AI-related technologies and systems for society, including consequentialism, deontological ethics, virtue ethics, ethics of care, and theories of justice. Such theories are often used to motivate the resulting normative principles for responsible AI systems, including those which deal with potential risks to human autonomy, safety, and privacy; uphold fairness, non-maleficence, and proportionality; promote social benefit, transparency, explainability, and robustness; and enhance trustworthiness and accountability. In many instances, the need for these principles is reinforced by the important requirements for responsible systems to be safe, reliable, secure, and of high quality. The quality of the datasets used for training AI systems, for instance, will be critical to limiting bias and ensuring representativeness.

Some of the ethical categories for responsible AI could be structured in a way aligned with the Complete Development Approach for regulation in general and the practice of AI regulation specifically. These categories would thus facilitate a sound choice of policy instruments and control mechanisms for particular systems and applications within a centralized governance model response, informing other response types as well.

### 6.2.2. Trust, transparency, and accountability

Creating and deploying AI systems that can be trusted—trusted to act ethically and in alignment with human values, trusted to function as intended, and trusted to be accountable when things go wrong—is a primary objective. Establishing trust in AI systems is critical to ensuring that people interact with such systems—and the decisions they make—without hesitation or doubt. Although trust in AI systems is a multidimensional concept, three aspects of trust are of concern: transparency, the capacity to ensure proper accountability throughout the life cycle, and the presence of appropriate and effective control mechanisms.

Transparency encompasses a fluid and holistic notion of explainability and interpretability. It pertains to the factors related to Data Quality, Bias, and Fairness (subsection 6.1), Clarity of Purpose (subsection 3.1), and understandability of the Interfaces (subsection 8.1). In a responsible AI ecosystem, suitable transparency measures support effective Accountability during the whole life cycle of the system. Accountability extends beyond the actors developing the system to include all participants, from policy-makers defining the context of use to individuals affected by the decisions made. In addition to being able to demonstrate that a system operates responsibly, these actors need to be able to specify and substantiate the measures put in place to ensure that the bespoke governance objectives are satisfied. Finally, it is important that the capacity to proffer Adequate and Effective Control (subsection 5.2) is not an afterthought; controls must be predefined, implemented, and integrated at each stage of the AI system's life cycle.

## 6.3. Governance Objectives and Stakeholders

Specific objectives for the governance of AI systems should be clearly articulated. In addition to safeguarding the interests of the public, private sector actors and other stakeholders, responsible governance requires measures to promote the democratic values of society at large, to minimize the concentration of power, and to safeguard public order and common security. Policy instruments for responsible governance should aim primarily at prevention, avoiding harmful outcomes at source, rather than developing post-hoc cures. This calls for public intervention well before, and independently of, any urgent crises or scandals.

In the AI domain, the boundary between the public and the private sector is increasingly blurred. Therefore, responsible governance requires an active engagement of policymakers, both in the regulation of private-sector activities and in the design and deployment of public-sector services. Both roles should be founded upon dialogue and co-design. Industry must bear responsibility for the effects of the application of AI

systems, independently of whether they are dynamic – that is to say, learning or evolving – throughout their life cycle. Producers should bear testing, certification and liability burdens commensurate with the level of risk entailed in deployment. Stakeholders' interests, including those of developers / service-providers, developers / service-users, individuals, the community, and society at large, should be considered during the development of AI systems.

### 6.3.1. Clear objectives for governance

When considering the governance of AI systems, it must be ensured that these systems are developed, used, and operated, in accordance with the governing principles and guidelines outlined in the United Nations Secretary General's Roadmap for Digital Cooperation and the relevant subsequent contributions. A key aspect of any responsible AI governance is clearly defined objectives for government action, policy, and investments in relation to AI systems.

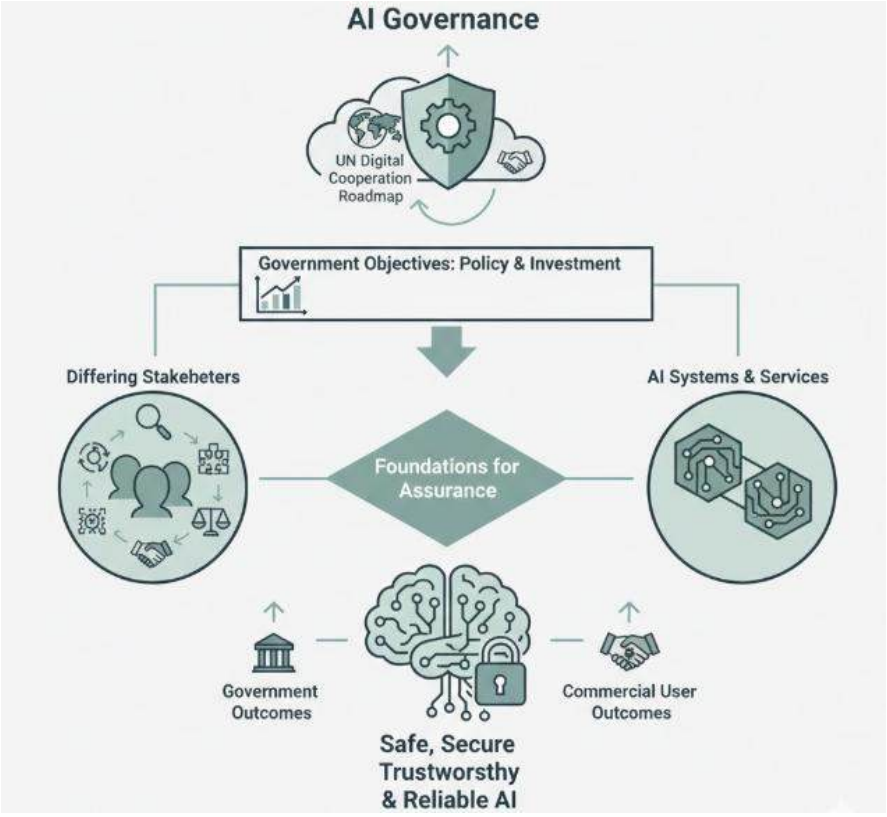


**Fig 6.2:** Foundational AI Governance: Harmonizing Global Policy Roadmaps with Stakeholder-Specific Assurance Frameworks

Depending on these choices, along with the actual systems used and in development, differing stakeholders can be expected to have differing relative needs for trust, transparency, and accountability, including greater or lesser emphasis on the use of different supportive foundations. Nevertheless, such foundations are ultimately expected to underlie required assurance of safe, secure, trustworthy, and reliable AI systems and services, thereby facilitating the outcomes sought by both governments and commercial users.

### 6.3.2. Roles of policymakers, industry, academia, and civil society

A broad, representative approach to AI governance must engage the diverse range of stakeholders with a legitimate interest in shaping the behaviour of AI systems. Policymakers can promote responsible behaviour by establishing appropriate legislation, funding, and other incentives, or by directly leveraging AI technology through the delivery of trusted public services. Private-sector actors have a key role to play by creating responsible products that consumers can trust, and industry initiatives can complement and inform regulatory approaches. Research in AI offers possibilities of risk mitigation, and creating technology-enabled assurance systems can contain and offset the consequences of AI systems being misused or operating dangerously. Civil-society organisations can help identify new risks and harm, and assist vulnerable populations in protecting themselves and accessing enforcement, oversight, and redress mechanisms. Such a broad coalition of stakeholders should collaborate to define and implement a governance framework that dynamically adjusts to the emerging risks and benefits of the technology.

Despite the large range of stakeholders who can contribute to governance and assurance, it is also important to ensure that the governance is not overly burdensome or convoluted. To avoid overly complex or burdensome governance, party primacy should be applied wherever feasible. Primary responsibility for enabling and assuring responsible use should be placed in the sectors and companies undertaking the most high-risk uses; the actors in these sectors are best positioned to monitor responsible conduct and establish effective self-regulation, and from a resources perspective the burden is also concentrated where it is most needed.

## 6.4. Governance Models for AI Systems

The governance of AI systems can take various forms and utilize different mechanisms, reflecting the risk associated with such technologies. Centralized models may be appropriate for specific use cases, such as the development of safety-critical systems, while decentralized models are more suitable for the general deployment of systems.

Different governance models operate with distinctive sets of control strengths and assurance mechanisms. Centralized models of governance can combine the greatest control strength with a holistic and systemic approach to assurance. In contrast, decentralized and multi-stakeholder governance arrangements rely on the concentrated investment of industries to develop regulatory mechanisms and instruments that best reflect the characteristics of AI technologies—thus providing the necessary assurance—and, on the other hand, enable it. Although this paradigm is not entirely absent from central systems with an external regulatory institution, its control strength is nevertheless lower than that achievable by purely centralized governance arrangements.

### 6.4.1. Centralized governance models

Centralized models of governance, in which public agencies or mandates hold clear authority over artificial intelligence systems, serve the objectives of control and assurance best when the stakes of potential failure are high. Policymakers can rely on a limited set of institutions and processes, allowing for a coherent approach to regulation, and direction of the system in alignment with legal values or national objectives. This may also be the most powerful means of guaranteeing change at scale and speed, and of coordinating other actors, including industry.

Centralized models appear appropriate for any real decision-making system that is explicitly intended to allocate power, direct hazard or misery, discriminate unfairly against someone, influence the direction of society or significantly displace existing employment and social patterns. Examples include autonomous weapons systems, and the use of judicial AI tools that decide on the detention and sentencing of accused persons. Yet centralized modes also apply in some less obvious instances: any decision-support system for magistrates, police, judges or parole commissions that influences the decisions of these authorities in a direction that departs from their own orders, foreseeing the social consequences of their collective decisions and their expected effect on society, is equally a candidate for centralized governance.

### 6.4.2. Decentralized and multi-stakeholder models

Decentralized and multi-stakeholder models of governance for AI systems offer another avenue towards achieving the objectives of trust, safety, and a beneficial system for society. These models include self-regulation for industry, regulation through litigation, adaptation of existing political models, and governance of the broader AI ecosystem.

Self-regulation in industry gives each company the choice on how an AI model should be implemented, except when legislation is ratified by a government agency. By

allowing companies the freedom to self-regulate, companies have more room for creativity and innovation to continuously improve the product. Although experts believe models such as these may lead to negligence of the principles laid out by society, the rationale behind adopting this governance model is that it remains flexible and close to the industry. However, a reconsideration of this model needs to happen as companies are currently achieving short-term money goals while neglecting long-term goals for the product, making self-regulation less efficient.

Regulation through legal means allows individuals or groups to make complaints about an AI system in court. If the issues are not resolved or if the AI causes damage or harm, damages are awarded to the plaintiff, establishing precedents for the proper usage of AI. This strategy is well known as ex-ante regulation and adapts the regulatory model commonly applied in patent law to the newly emerging AI sector. An AI regulation governance strategy that reflects the general conception is also considered reasonable: possible breakthroughs in AI development need control and precaution. The emergence of self-driving cars acts as a strong evidential reference. The field of traffic law is adapting for the new era of self-driving technology, as it must make provisions from scratch. The opinion is to adopt an adjustment way in the evolving period without a dedicated supervisor law.

### 6.5. Mechanisms of Control and Assurance

The overarching principle of governmental control and assurance regarding the responsible use of Artificial Intelligence is that the use of AI systems must indeed benefit society at large. It is critical to ensure that the power and effectiveness of these systems are to the great advantage of humans in our societies. In this context, a) the nature of the policy instruments and regulatory mechanisms that are required to moderate the development and deployment of AI technology at different points in the life cycle remain under examination, and b) technical controls requiring such systems to be safe, reliable, capable of being controlled, and robust are discussed.

The Governance Models Group identifies two mechanisms of control. Control of AI systems is characterized by the devices and methodologies that policy-makers, corporations, institutions, and civil societies set in place to exert a direct, authoritative influence on the development and deployment of the technology. Policy instruments and regulatory mechanisms that govern the development and deployment of AI systems fall primarily within the domain of centralized governance models, although these centralized mechanisms would be consistent with more decentralized, multi-stakeholder governance models. Second, technical controls are characterized by the measures that the technology developers and deployers emphasize in order to maximize both society's trust in the technology and the safety of its operation at scale.

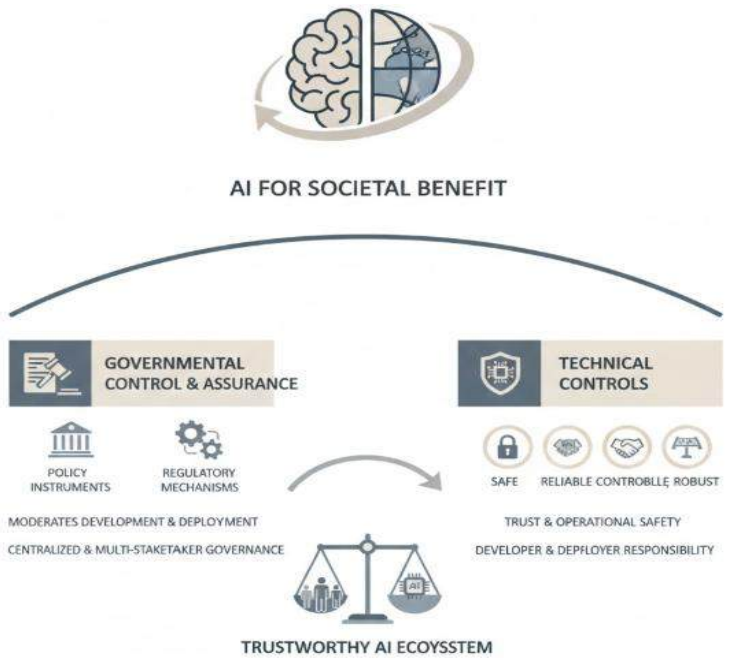


**Fig 6.3:** Bridging Policy and Provenance: A Dual-Mechanism Framework for Centralized Governance and Technical Control in Trustworthy AI

### 6.5.1. Policy instruments and regulatory mechanisms

Governance mechanisms play a critical role in bringing the principles of responsible AI from a high-level definition into concrete implementation throughout the lifecycle of the systems being developed and deployed. However, at present, many practical governance implementations focus primarily on the technical controls outlined previously or on establishing an assessment framework based on risk categorization, with far less focus on the accompanying policy instruments and regulatory mechanisms needed to ensure that the action-oriented principles are actually upheld in practice. Policies enable us to define the acceptable parameters of AI system development and deployment within which designers, developers, providers, and operators can exercise the technical controls on the AI systems. Policy instruments can take the form of law, legal testing, moratorium, and self-regulation, although they also encompass broader governance mechanisms such as codes of ethics, model regulations, auditing protocols, and so on.

Regulation is not a new concept for the domain of information technology: the architecture itself acts as a regulatory mechanism. The distribution of access to the knowledge and processes for creating models that treat illicit content mitigates the potential harmfulness of badly-behaved systems even at an architectural level. The principle itself is established in the European Union on the Sofia Declaration. Legal

rules, though, enjoy the advantage of explicitness and durability and gain further strength and importance when viewed as being established within an Active Environment, one in which experience-based redefinability ensures that legal rules can evolve to reflect both cross-constituency ethical sensitivity shifts and the effects of unforeseen, unintended AI impacts. In templatized areas like AI safety-reliability-robustness, the civil-society policy instruments of Legal Testing, Normal Testing, Case Checking, Case Physics, and Sump-Mapping serve to specify the legally defined class of the system and the legally defined fate of badly-behaved members of that class, information that can then be parameterized into model Auditing Protocols enabling their widespread, undelayed application.

### 6.5.2. Technical controls: safety, reliability, and robustness

Control and assurance mechanisms also comprise technical controls aimed at improving the safety, reliability, robustness, and security of AI systems in order to limit adverse impact and prevent harm. Along with the implementation of appropriate technical controls, these approaches include validation, verification, and testing throughout the lifecycle of AI systems, as well as corrective action that can be taken after deployment. Such mechanisms should focus on the systems' purpose, operational environment, expected application, and possible interactions with other systems. Audiovisual content generation and manipulation is an implicit safety concern against which technical controls can offer guarantees.

Addressing the technical safety and robustness of advanced AI systems subject to unpredictable and potentially harmful emergent behaviours constitutes an enormous challenge. Scale and complexity shrink the probability of an unforeseen harmful behaviour but enlarge its consequence, and responsibility usually remains unattributed. Different classes of behaviours (including greater magnitudes and values beyond specified ranges) and classes of failure (particularly those that endanger human life, are illegal, or contravene explicit limitations) require qualitative treatments distinct from mere incremental improvements in utilities and reliability.

Important technical desiderata for such advanced systems include the containment and control of possible catastrophic behaviours, the certainty of real-world properties (safety, etc.), a natural and effective alignment of interests and goals with humans, a principled approach to the specification of norms and values in complex circumstances, systematic approaches to quantifying uncertainty, security and safety in the face of uncertainty, the detection and logging of significant events, and principles for the natural exploitation of uncertainty in human and animal-like behaviours.

## 6.6. Data Governance and Privacy Considerations

Ensuring data quality, representativeness, and adequacy for the intended tasks is necessary to reduce biases, improve safety, and increase users' trust in AI systems. All datasets used for training and testing AI systems should be free of covertly discriminatory entries and be adequately representative with respect to the demographics and characteristics of the populations on which these systems will operate. In this regard, representative sampling should also be complemented with accurate and non-biased labeling of datasets. Furthermore, AI systems should include bias indicator detection capabilities, alerting users to potential model limitations, undersampling of minority groups, or over-representation of certain biases. Such indicators should also point to the presence of additional risk sources, besides model bias, which may aggravate harm impact for sensitive subgroups.

Data ownership, access, and consent are predominant issues for many of the AI guidelines and frameworks that span the full AI lifecycle. The evolution of AI systems is potentially determined by the scarcity of large, high-quality datasets needed to train, validate, and test these systems. To allow the sharing of data and mitigate biases, yet preserving privacy and confidentiality, responsible AI governance models should define frameworks for secure, transparent, and accountable data accesses, transactions, sharing, and monetisation across sectors. These frameworks should balance between allowing the sharing of proprietary datasets and the protection of trade secrets and ensure that the data are used according to the informed consent of the individuals represented in the dataset.

### 6.6.1. Data quality, bias mitigation, and representativeness

Poor quality datasets likely lead to unreliable AI systems. Measures to ensure high data quality across all lifecycles and types of datasets should be integrated into responsible and trustworthy AI solutions. Industry, government, and academia should invest more in evaluating datasets that are used in the development phase of AI systems, especially in the preparatory phase or early design stage, following the findings of the AI4People crowdsourcing initiative. Besides the label of data quality, the bias mitigation label has also reached its maturity. It aims to highlight the datasets that applied bias mitigation methods during construction either directly or indirectly. A very recent and internationally-called request has emerged in the AI for Climate Action initiative that demand datasets on climate environmental change, disaster risk and reduction, biodiversity and/or ecosystem assessment, and climate adaptation and resilience, following the call to action for AI for Good issued by the UN. Indeed, representativity is financed and prioritized by many private sectors, including Meta, which focuses its

support on immigrant and rainbow communities, while Google focuses on problems related to healthcare and accessibility.

The connection among these labels is found to be crucial in further sustainable AI application development. In addition, some labels systems have been developed to flag datasets that are available in the society's interest. One example of these categories is the Data For Good community, where the initiatives aim to give life to open datasets covering crucial societal issue related to climate, health, human rights, and poverty by connecting data owners/devices and distinct stakeholders to write guidelines of human-centered datasets. A step further in the generations of high-quality datasets with more than one functional objective includes the Data Responsibility Community, created on Github to create and maintain a living platform that helps data providers and users to create higher quality, risk-aware datasets.

### 6.6.2. Data-access, ownership, and consent frameworks

A significant aspect of responsible AI systems involves a careful examination of data-access, ownership, and consent frameworks. Currently, the available datasets that serve as the foundation for the training and evaluation of AI systems are closed, proprietary, and poorly documented or curated. This lack of transparency not only diminishes researchers' understanding of the properties of the datasets, but also hinders their exploration for the identification of ethical and societal impacts. Proposals have emerged to implement a data-access board that would operate similarly to an institutional ethics committee and would grant access to key AI datasets and/or models only to those researchers who document an ethical research agenda and obtain funding to support the research.

Furthermore, as AI systems become powerful tools for data generation and insight extraction, different ownership models, such as data commons, should be explored. In this sense, objective-sharing principles—such as those guiding crowd-based initiatives like the Human Genome Project—may help the AI community move in the right direction with respect to pooling and sharing datasets and AI models for public interests. Sharing data and AI models can foster natural monopolies and prevent unnecessary duplication of research investments, but a degree of data access is also essential to ensure that these powerful tools operate responsibly, safely, and easily adopted by society.

Addressing ownership questions requires a focus on answers to two fundamental questions that have surfaced with the emergence of generative AI: Who owns the new data generated with generative AI? and Do the users of generative AI platforms have? Companies must address the concerns related to users' ownership of the new content created using their proprietary models; and an updated data-ownership framework

should be designed to address all relevant aspects of data ownership in the context of generative AI data. Finally, special attention must be given to how consent is obtained from contributors to datasets containing human information and how this consent is respected and acknowledged when data are manipulated or transformed by AI models.

## 6.7. Conclusion

In summary, the governance of AI systems is an urgent issue that needs to be addressed. A careful analysis of existing and emerging governance frameworks highlights the need for a combination of approaches designed to achieve the ultimate governance objectives. Centralized models enable powerful policy instruments to be established with accountability, clarity, and monitoring. Decentralized and multi-stakeholder models ensure that norms emanate from a participatory process that can enhance legitimacy. Nevertheless, the critical governance objectives cannot all be achieved in the same manner. Controls and assurances are needed to address the remaining governance challenges. Policy instruments and regulatory mechanisms, whether general or specific to certain AI capabilities, can control the responsible development of AI systems with an adequate mechanism for laws and regulations to keep pace. Technical controls and assurance measures related to safety, robustness, and reliability provide assurances on the risk and harm of particular AI systems and capabilities. Risk and safety-focused evaluations can help build trust where it is lacking.

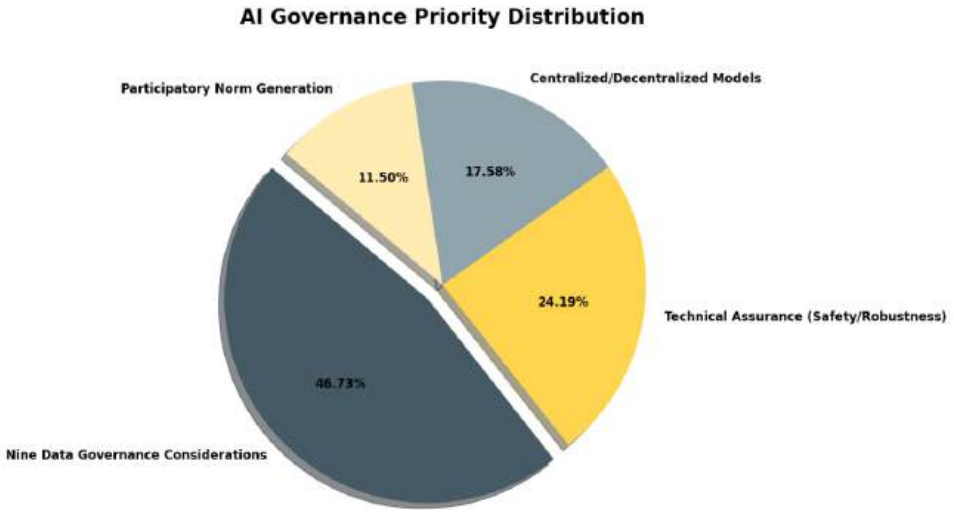


**Fig 6.4:** AI Governance Priority Distribution

Governance of AI systems is also a data governance issue. AI systems rely heavily on data for their decision-making. Poor data quality can lead to an entire system that lacks safety, trustworthiness, and robustness and that generates harmful decisions. Moreover,

AI systems are used to inform and enhance decisions that have serious impact on individuals and society; thus, bias and representativeness issues can obviously not be ignored. Nine considerations for data governance illustrate the key issues: quality assurance and bias mitigation in data; general framework addressing data-access, ownership, and consent issues; representativeness in dataset generation; data protection and privacy; preserving value of private data; balancing individual privacy with group privacy; preserving insurance state; insurance-challenge provisions for leakage of sensitive data; and privacy-preserving sharing and synthesis frameworks for AI-specific datasets.

### 6.7.1. Final Reflections and Future Directions in Responsible AI Governance

The current discussion has provided an overview of the main principles underpinning Responsible AI and identified the key objectives related to the governance of AI systems. Considering the broad societal implications of AI systems, it is crucial to define what is being governed, the roles and responsibilities of different actors, and the impact of AI systems on different stakeholders. A tempting but superficial response to these questions might be a single governance model that applies to all AI systems, which logically leads to recommendations for specific policy instruments. However, this approach misunderstands the need for Responsible AI.

Responsible AI is not about the regulation of AI systems; rather, it is about a structured assurance of the Responsible realisation of future AI systems that guarantees their trustworthiness. Therefore, the governance of AI systems requires a layered approach that considers differing degrees of risk from AI systems and matches those with proportionate and targeted governance structures, mechanisms of control, and assurance. Past experience with technological innovation warns against restrictive centralised systems for deployment and use. Such systems are prone to regulatory fatigue as they attempt to preemptively govern whole classes of technology that are not yet fully understood. Censoring current AI systems shuts down innovation and restricts useful applications, whereas the absence of regulation can easily lead to harm.

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