Operationalising AI safety: A lifecycle approach

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NATIONAL LAW UNIVERSITY DELHI

Prof. (Dr.) G.S. Bajpai
Vice Chancellor

Foreword

The unprecedented proliferation of AI systems has led to their integration across several high-stakes functional applications. While the merits of AI are extensive, ranging from scientific breakthroughs to enhanced productivity, they are often accompanied by unique challenges that require rigorous oversight and preparedness. It therefore becomes essential to strike a fine balance between acknowledging the extraordinary potential of artificial intelligence and the responsibility of managing the impending risks. From a Global South perspective, where the impact of AI is deeply intertwined with infrastructural challenges and unique cultural contexts, establishing a robust framework for responsible AI deployment is an imperative for identifying risks that lie beyond the scope of technical metrics.

AI safety encompasses robust standards and evaluative methodologies to align AI development with the collective interests of society, thereby minimizing the probability of unanticipated detrimental outcomes. The field of AI safety can play a major role in shaping the trajectory of responsible AI adoption in the Global South, which is characterized by linguistic diversity, resource constraints, and an increasing need to focus on social empowerment.

AI safety is no longer a field solely falling within the realm of theoretical computer science, having far-reaching implications facilitated by the large-scale adoption of AI across different domains. With AI safety having established itself as a prominent field, this new report - *'Operationalising AI Safety: A lifecycle Approach'* from the Centre for Communication Governance at the National Law University Delhi with support from Konrad-Adenauer-Stiftung presents a meticulous and systematic evaluation of the evolving landscape of this field. By attempting to offer insights to a diverse range of stakeholders, this report can aid in creating awareness and contributing meaningfully in shaping the global dialogue within international governance forums. Part I of the report explores the various conceptions of AI safety followed by delving into the evolution of the concept. By examining the contemporary debates and challenges with interpretations within the field of AI safety, this report advocates embracing a socio-technical approach to it associated with the contextual nuances of the Global South.

Part II of this report explores how AI safety is operationalised through a lifecycle approach. By mapping the AI lifecycle, this report identifies specific risks and harms inherent to each developmental stage. The report also examines key corresponding governance mechanisms for each stage, while providing insights on how these mechanisms are reflected in legal frameworks. The report concludes with elaborating on key considerations for the Global South with respect to the implementation of the governance mechanisms by highlighting the contextualised challenges, local realities, and experiences from the Global South.

This timely report is intended to serve as a reference for a wide spectrum of actors across the AI ecosystem including academicians, technologists, civil society groups and policymakers. As Vice Chancellor of the National Law University Delhi, I commend the Centre for Communication Governance's vision in synthesizing scholarship that engages closely with emerging global issues. This report showcases the Centre's commitment to policy-relevant research that integrates scholarly research, governance and public advocacy.

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With India set to preside over the AI Impact Summit this year, we have a pivotal window to prioritize the operationalization of AI safety while ensuring that Global South equities are at the heart of the discourse. The Summit also offers a critical opportunity for India to help shape the trajectory for responsible development and deployment of AI for the Global South. It is imperative for the Global South priorities and interests to play a major part in informing and tuning the global AI safety policy discourse.

(G S Bajpai)

Prof. (Dr.) G. S Bajpai

Vice Chancellor, National Law University Delhi

Note to Reader

This report is part of the Konrad-Adenauer-Stiftung (KAS) Rule of Law Programme Asia's ongoing work on the governance, safety, and social impact of artificial intelligence.

It is released at a particularly timely moment, as it is launched alongside the India AI Impact Summit, when global debates on AI are marked by heightened momentum, visibility, and urgency. The AI Impact Summit has brought together policymakers, industry leaders, civil society, researchers, and technical experts from across regions, generating strong traction and dynamic exchanges on how AI systems should be developed, governed, and deployed. Launching this report in parallel with the Summit allows its analysis to resonate with ongoing discussions, benefit from heightened interest and attention, and contribute meaningfully to shaping emerging narratives and policy priorities around AI safety at both regional and global levels.

AI safety is closely linked to AI security and AI ethics. While AI safety refers to the practice of ensuring that AI systems operate reliably, predictably, and without causing unintended harm, AI security deals with protecting systems from misuse, attacks, and malicious actors. AI ethics, in turn, addresses broader questions of fairness, accountability, transparency, and respect for human rights. In practice, these areas often overlap and cannot be treated separately.

The goal of this report is to move beyond purely technical understandings of AI safety. It adopts a holistic, lifecycle-based and socio-technical approach, analysing how risks and harms can arise at every stage of the AI lifecycle, from early planning and data collection to deployment and post-deployment monitoring. For instance, during the data collection stage, AI developers are encouraged to keep detailed records of where data comes from, how it was collected, and whether consent was given. They should also audit the data for fairness and accuracy. This ensures that models are trained on trustworthy and representative data, reducing the risk of bias or unsafe outcomes later. This example illustrates how AI safety is a step-by-step process that combines technical measures with good governance.

The report shows how these risks are shaped not only by how models are built, but also by laws, governance structures, institutional choices, and social and political contexts. By focusing on real-world, longer-term and systemic risks, and by paying particular attention to Global South contexts, the report aims to support more practical and inclusive approaches to AI safety.

For the KAS Rule of Law Programme Asia (RLPA), working on AI safety is both timely and central to its mission. AI systems are increasingly used in areas that are fundamental to the rule of law, including public administration, law enforcement, education, healthcare, elections, or access to justice. When AI systems are poorly governed, opaque, or unsafe, they risk reinforcing existing inequalities, enabling discrimination, weakening procedural fairness, and undermining trust in public institutions. These risks are particularly serious in contexts where legal safeguards and oversight mechanisms are still developing.

At the same time, when AI is being developed and governed responsibly, it can strengthen institutions and improve the delivery of public services. Engaging with AI safety allows the RLPA to connect technological developments with core rule of law principles such as legality, accountability, transparency, proportionality, and the protection of fundamental rights.

The outcomes of the AI Impact Summit, whether new governance frameworks, institutional initiatives, or shifts in international policy debates, will strongly influence how AI safety is understood and implemented in the years ahead, including the role of Global South leadership in AI governance. Insights and developments from the Summit will also inform the next phase of research under the KAS Rule of Law Programme Asia, helping to identify new research priorities, and deepen engagement with regional perspectives.

In this sense, this report is not a final statement, but a contribution to an ongoing and evolving body of work. It is intended to support continued learning, dialogue, and collaboration as AI systems become more deeply embedded in societies across Asia and beyond.

Stefan Samse
Director, KAS Rule of Law Programme Asia

Olivia Schlouch
Programme Manager, KAS Rule of Law Programme Asia

About NLUD

The National Law University Delhi is one of the leading law universities in the capital city of India. Established in 2008 by an Act of the Delhi legislature (Act. No. 1 of 2009), the University is ranked second in the National Institutional Ranking Framework for the last five years. Dynamic in vision and robust in commitment, the University has shown terrific promise to become a world-class institution in a very short span of time. It follows a mandate to transform and redefine the process of legal education. The primary mission of the University is to create lawyers who will be professionally competent, technically sound and socially relevant, and will not only enter the Bar and the Bench but also be equipped to address the imperatives of the new millennium and uphold the constitutional values. The University aims to evolve and impart comprehensive and interdisciplinary legal education which will promote legal and ethical values, while fostering the rule of law.

The University offers a five-year integrated B.A., LL.B. (Hons.), a one-year postgraduate masters in law (LL.M), and a Ph.D. program, along with professional programs, diploma and certificate courses for both lawyers and non-lawyers. The University has made tremendous contributions to public discourse on law through pedagogy and research. Over the last decade, the University has established many specialised research centres, and this includes the Centre for Communication Governance (CCG), Centre for Innovation, Intellectual Property and Competition, Centre for Corporate Law and Governance, and Centre for Criminology and Victimology. The University has made submissions, recommendations, and worked in advisory/consultant capacities with government entities, universities in India and abroad, think tanks, private sector organisations, and international organisations. The University works in collaboration with other international universities on various projects and has established MoU's with several other academic institutions.

About CCG

The Centre for Communication Governance at the National Law University Delhi (CCG) was established in 2013 to ensure that Indian legal education establishments engage more meaningfully with information technology law and policy and contribute to improved governance and policy making. CCG is a leading academic research centre dedicated to undertaking rigorous academic research in India on information technology law and policy in India. Through its academic and policy research, CCG engages meaningfully with policy making in India by participating in public consultations, contributing to parliamentary committees and other consultation groups, and holding seminars, courses and workshops for capacity building of different stakeholders in the technology law and policy domain.

The Centre has had multiple publications over the years including reports on Exploring AISIs for the Global South, The Road to WSIS+20: Key Country Perspectives in the Twenty-Year Review of the World Summit on the Information Society (India Chapter), Platform Transparency under the EU's Digital Services Act: Opportunities and Challenges for the Global South, Social Media Regulation and the Rule of Law: Key Trends in Sri Lanka, India and Bangladesh, Intermediary Liability in India, a report Mapping the Blockchain Ecosystem in India and

Australia, a UNDP Guide on Drafting Data Protection Legislation, a book on Privacy and the Indian Supreme Court. The Centre has launched freely accessible online databases - Privacy Law Library (PLL) and High Court Tracker (HCT) to track privacy jurisprudence across the country and more than sixteen jurisdictions across the globe. CCG also has an online 'Teaching and Learning Resource' database for sharing research-oriented reading references on information technology law and policy. In recent times, the Centre has also offered courses on AI Law and Policy, Technology and Policy, and first principles of cybersecurity.

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Section I

Conceptions and Elements of AI Safety

A. What does AI safety mean?

AI has achieved ubiquity across various domains, establishing itself as an effective tool for enhancing human capabilities and propelling its adoption across several high-stakes scenarios such as healthcare, financial markets, and public welfare. However, these rapid advancements have also paved the way for unchecked harms, inconsistent outcomes, and safety concerns raising apprehension among users, governance bodies, civil society groups, academia, AI researchers and policymakers.[1] The accelerated developments in the field of AI and the widespread adoption of Large Language Models (LLMs) have also highlighted its propensity for perpetuating harms including bias, privacy breaches and rampant spread of misinformation.[2] Notably, the perceived existential dangers from advanced AI have also contributed towards prioritising research on AI alignment[3] within major tech companies. The imperative to deliberate on AI safety has escalated, necessitating a comprehensive examination of the multifaceted risks inherent in AI design and deployment, as well as the development of efficacious mitigation strategies to address attendant or associated harms.[4]

In two sections, this report explores conceptions and discourse related to the notion of AI safety and subsequently, examines how key elements of AI safety are operationalised within the lifecycle of AI development and deployment. Section I of the report explores the various conceptions of AI safety followed by examining the evolution of the concept of AI safety. This section synthesises current debates and articulates a shift towards a socio-technical approach, hence ensuring that safety mechanisms are contextualised to the unique complexities of the Global South. Section II of the report delineates the methodologies for operationalising AI safety through a lifecycle approach. By dissecting the different stages of the AI lifecycle, the report offers insights on the critical risks relevant to each stage, the corresponding technical and governance interventions that can be designed for risk mitigation, and key considerations for the Global South.

B. Methodology

For the purpose of Section I in this report, we have examined existing literature to summarily capture the evolution of conceptions and risks associated with the field of AI safety. In Section II, we have adopted a skeletal lifecycle approach to identify and situate risks and governance measures in the development and deployment of an AI system. This discussion has involved examining existing academic and technical literature, policy reports, and legal analyses of relevant regulatory instruments. We have merged certain stages of the lifecycle since the risks and governance measures across these stages shared key qualities and had significant similarities. The stages classified have been isolated based on distinct identifiable harms and corresponding mitigation measures. These stages can be broken down further, but for the purposes of our research, the five stages identified are Inception and Planning, Data Collection and Preparation, Model Design and Training, Verification and Validation, and Deployment and Post-Deployment. In each stage, we identify pertinent risks, discuss key mitigation measures from a technical lens and where applicable, global regulatory efforts. Critically, we highlight the socio-technical harms that can present with AI systems, and what these harms and mitigations efforts look like, in particular, for the Global South. With a sub-section on 'Considerations for the Global South' under each stage, we seek to contextualise and highlight the unique challenges and lived realities to account for when deploying AI systems in this part of the world.

It is pertinent to note that the report was designed with certain limitations in consideration. Given the nascent stage of regulatory frameworks for AI, and the limited publicly available information on initiatives beyond the EU, UK, and US, this report draws heavily on regulatory provisions and examples from these three regions. Moreover, while this report introduces and acknowledges the importance of key actors in the AI lifecycle, it does not discuss risk and mitigation measures through this lens.

As part of our research for this report, we engaged with expert stakeholders and conducted interviews. Insights from our stakeholders have been anonymously attributed. Our stakeholders include Tarunima Prabhakar, Founder, Tattle Civic Technologies; Rafael Zanatta, Director, Data Privacy Brasil; Catherine Setiawan, Country Coordinator, Global Index on Responsible AI; Diane Chang, Senior Fellow at Tech Global Institute; and Kalika Bali, Senior Principal Researcher at Microsoft. This research has also involved stakeholder engagement through an event on 'Operationalising AI Safety' held at New Delhi on 6 November 2025. The panel and roundtables saw participation from a diverse range of stakeholders from the Global South, across sectors including industry, government, academia, and civil society. This event marked the report launch of our report, titled 'Exploring AISIs for the Global South.' The event provided an introduction to CCG's exploration and research findings from the report, including considerations for upcoming AISIs in the Global South. Building on this, the discussions at the panel and roundtables shaped insights for this report and provided further clarity on how AI safety is operationalised across the life cycle, and key considerations for the Global South.

C. How did the field of AI safety evolve?

The rise of AI automation sparked theories regarding machines' capability to generate unforeseeable decisions and surpass human control as early as the 1960s.[5] [6] Research highlights how some artificially intelligent agents, in their quest to accomplish and optimise for certain concrete end-in-itself goals,[7] were touted to value self-preservation and work strategically towards ensuring their own survival.[8] Commencing in the early 2000s, the conversations around mitigating the potential protracted effects of superintelligence and futuristic propositions related to Artificial General Intelligence (AGI)[9] marked the beginning of AI safety as a formal discipline.[10]

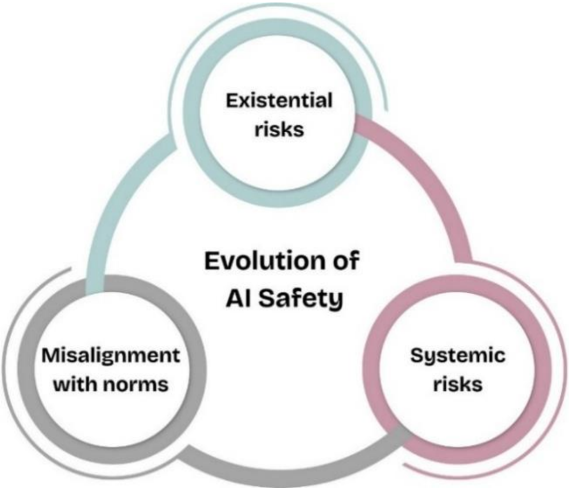


Figure 1: Evolution of AI Safety: Risks

i. *Addressing existential/ catastrophic risks*

By the mid-2000s, the prominent objective of the AI safety domain was to ensure that the use of AI machines did not culminate in harmful outcomes while contributing positively to the progress of the human race.[11] This period was followed by the beginnings of a growing consensus among a section of AI researchers that advanced AI would likely become a major source of existential risk.[12] The capability of AI tools to deliver critical information for designing weapons of mass destruction, launching cyberattacks, and affecting political stability through manipulation and misinformation are some of the examples cited by recent literature to reinforce focus on existential risks.[13] The narrative around AI potentially culminating in existential and catastrophic risks to humankind remains a heavily debated topic in research circles and continues to be instrumental in shaping the public discourse on AI safety.[14] [15]

The inflated projections around the inevitability of AGI-led apocalypse and the potential gains stemming from AI's transformative potential have also garnered interest and support from a movement, popularly termed as effective altruism.[16] The effective altruism community prioritises the promotion of a research agenda on technical AI safety, thereby steering the focus away from the consequences of an increasing corporate power asymmetry.[17] Extensively funded by tech billionaire donors and primarily driven by Silicon Valley AI companies, this ideology has been instrumental in racing to create precarious AI systems under the garb of AI safety. For instance, under the pretext of developing AI applications beneficial to humankind, tech companies have been contributing to unchecked risks by prioritising rapid deployment over rigorous safety testing, and obfuscating ambitions of securing supremacy in the global race for AGI.[18] [19] This heightened and insular focus on mitigation of AI-fuelled techno-utopianism[20] (a claim largely unfounded) associated with emerging AI also distracts and takes the attention away from genuine immediate harms warranting attention. [21] One of the most prominent focus areas for the effective altruism community also includes addressing technical alignment issues, identified as one of the many factors potentially leading to catastrophic risks to humanity.[22]

ii. The alignment problem

AI systems persistently encounter challenges related to alignment - a concept dating back to the 1960s, and which has emerged as one of the prominent sub-fields in the field of computer science.[23] The alignment problem translates as the inability of AI systems to internalise, optimise and represent the values and objectives defined by the human developer.[24] Ensuring that an AI system captures human values and norms, while understanding and behaving as expected, also forms a crucial objective in the field of

AI safety. Mis-specification of subgoals and misaligned objectives during the training and development of an AI system can prove risky, especially in scenarios where a system begins to pursue objectives outside the scope of its human-defined mission.[25] Reward hacking highlights one such instance of misalignment in AI systems, where in its quest to achieve a higher reward (separate from the intended reward outcomes), an AI agent is observed to resort to shortcuts by exploiting flaws in the design of the reward function.[26] Additionally, the complexity and subjectivity of human values also presents a significant hurdle for aligning AI in the absence of a universal agreement on the set of values that should be encoded into AI systems.[27]

iii. The need for a Socio-technical approach

Technical literature on AI safety takes a narrow approach while enumerating the objectives under the discipline of AI safety. It broadly categorises challenges to accuracy, robustness, reliability and security as the crucial components under this field.[28] This framework further lends credence to the assertion that AI safety efforts are exclusively technical. However, contemporary studies on AI safety highlight how the discipline also forms an intrinsic part of the larger structure of trust and responsibility,[29] and comprises ethical considerations including fairness, accountability, data privacy, bias mitigation and transparency, which are some of the key tenets of Safe AI development.[30] Algorithmic fairness is defined as a social construct, involving designing solutions to address the systemic harm that algorithms can inflict disproportionately on specific groups.[31] While robustness is characterised as a model's resilience against adverse circumstances,[32] the reliability of a model is measured in terms of its consistency of outputs and reduction in system failures.[33] Model transparency is the property that enables understanding the inner workings of a model, a crucial facet due to an AI system's inherent "black-box" nature. Explainability, on the other hand, aids in enhancing clarity on the rationale behind the decision-making process employed by an AI system.[34]

Further, the interdependencies between technical design decisions, system deployment contexts, and existing social hierarchies have also contributed to how technical systems shape and in return are shaped by societal power structures.[35] This perspective necessitates reframing traditional approaches to facilitate better management of risks under the domain of safety by adopting an alternative paradigm rooted in socio-technical discourse.

The adoption of AI has culminated in broader systemic risks[36] across the AI lifecycle due to intermingling with real-world social, political, and cultural dynamics. This has in turn contributed to structural harms being embedded right from the training stage of an AI system. The utilisation of underrepresentative datasets and the consequent effects of algorithmic bias have also resulted in skewed outcomes, discrimination, privacy breaches[37] and copyright violations.[38] The deployment of algorithmic decision-making for public welfare has also led to concerns of the amplification of centralised forms of state and private control.[39] Additionally, the widespread integration of AI across different applications has led to labour market disruption,[40] and human rights concerns owing to the harsh, inequitable and extractive working conditions under which the data annotators are made to operate.[41] This large-scale deployment of AI also carries substantial environmental implications, chiefly driven by the energy demands of AI infrastructure such as data centres and powerful transformer models.[42] All these contribute to an expanding carbon footprint,[43] [44] negatively impacting the living conditions of vulnerable communities inhabiting the surrounding areas.[45] [46]

Given that the array of risks falling within the ambit of AI clearly encompasses systemic risks and unforeseen downstream harms to society, safety cannot be conceptualised to hinge on purely technical approaches and emphasis on combating existential risks. Interdisciplinary scholarship also highlights how the domain of AI safety cannot solely depend on optimising technical design and focusing on the model property of an AI system[47] Emphasising that safety of an AI system is also largely contingent upon its deployment context, concerned stakeholders and institutional environment, research points out the significance of embracing a socio-technical framing to AI safety.[48] A sociotechnical approach understands that the efficacy and safety associated with any technology is always the result of not just technical features but also larger societal forces, and takes into consideration factors such as institutional governance, human labour and social conditions.[49] Taking a socio-technical approach can therefore enable the creation of solutions embedded with societal insights by ensuring stakeholder engagement from diverse domains. Opting for participatory models involving impacted communities can also support AI systems in functioning effectively by minimising reliance on technological workarounds alone.[50] [51]

The field of AI safety needs to be broadly conceptualised to incorporate a holistic framework encompassing a wide spectrum of harms and a diverse range of values and approaches to address these harms effectively.[52] Research has expanded the scope of this academic discipline by necessitating consideration of not just technical aspects such as model alignment, or research on existential risks, but also recommendations for regulating the governance of AI for mitigating social harms.[53] In other words, AI safety research must accord equal significance to the full spectrum of AI-generated risks, encompassing both technical issues (such as unsafe exploration [54] and distributional shift[55]) and social harms (including bias and discrimination) to examine how it engages with people, systems and processes.[56] The notion of AI safety must be contestable for it to be conceptualized and reinterpreted by different communities in accordance with their goals and aspirations.[57]

D. How is AI Safety defined?

AI safety is a nascent, emerging and conceptually disputed field open to various interpretations by different stakeholders. It has been defined as a research discipline entrusted with the prevention or minimisation of risks emanating from the development and implementation of AI systems.[58] In the technical sense, it has also been described as an area investigating causes of unanticipated outcomes in AI systems[59] and conducting research focused on optimising the benefits of AI integration.[60] This field also encompasses mitigation of accidental risks resulting from unforeseen divergence of AI systems from their intended behaviour.[61]

Delineation and convergence within the fields of AI ethics, AI safety and AI security

Literature on AI attempts to delineate AI safety with two closely related but distinct fields - AI ethics and AI security - depending on their core functions and the category of harms these fields seek to address. The field of AI ethics is well-established and has been defined as a collection of principles, values, and methods that applies accepted standards of morality to the development and application of AI.[62] Principles including fairness, transparency, explainability and privacy have been categorised under the ambit of AI ethics. This discipline typically concerns itself with mitigation of present-day harms[63] (bias, discrimination and privacy invasion, for instance) momentarily plaguing algorithmic systems.[64] AI safety, on the other hand, has been ostensibly linked with the design of interventions aimed at resolving prospective challenges (strengthening robustness of a system, for instance) inherent in evolving algorithmic systems.[65]

Research also points to a lack of consensus in the category of risks falling under the ambit of AI safety and AI security. AI security is a characteristic of a system for exhibiting resilience against malicious attacks on the system components and operations, and ensuring that the integrity of the system is preserved in the face of adversarial actions.[66]

According to scholarly analyses, AI safety must typically concern itself with unintended or accidental harms arising out of AI systems, such as misalignment, design flaws and embedded biases, while AI security is purportedly entrusted with the aim to build resilience in AI systems against malicious actors and intentional adversarial acts (jailbreaking, for instance).[67]

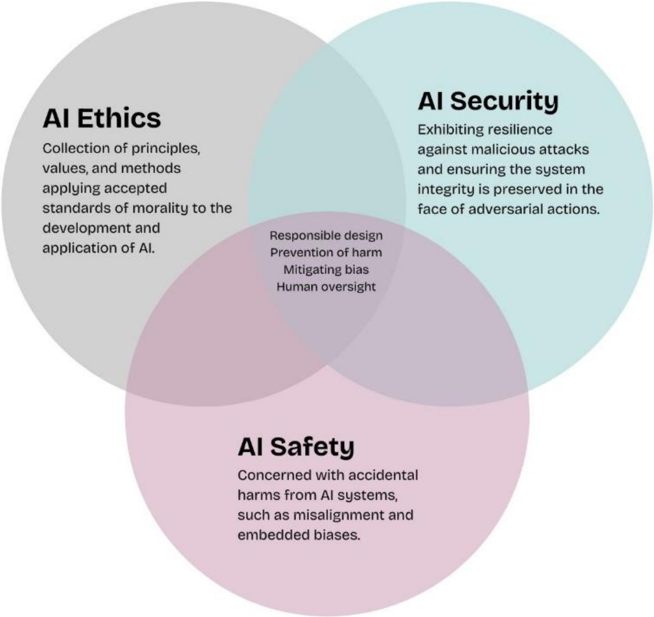

AI Ethics
Collection of principles, values, and methods applying accepted standards of morality to the development and application of AI.
AI Security
Exhibiting resilience against malicious attacks and ensuring the system integrity is preserved in the face of adversarial actions.
Responsible design
Prevention of harm
Mitigating bias
Human oversight
AI Safety
Concerned with accidental harms from AI systems, such as misalignment and embedded biases.

Figure 2: Delineation and convergence within the fields of AI ethics, AI safety and AI security

However, recent discourse on AI emphasises the necessity of integrating these disciplines given their overlapping boundaries and challenges in delineating both risks and solutions, to more effectively mitigate the contextual harms posed by AI systems.[68] [69]

E. Status quo and relevance for the Global South

The meteoric popularity and large-scale deployment of LLM applications has also acted as a catalyst for prompting urgent discussions amongst jurisdictions and policymakers worldwide around developing the field of AI safety.[70] The first AI Summit hosted by the United Kingdom at Bletchley Park in November 2023 was instrumental in ushering the issue of AI safety and the risks posed by frontier AI to the forefront.[71] This Summit also led to the establishment of the first AI Safety Institute[72] (AISI) in the UK, which was followed by multiple jurisdictions launching their own AISIs.[73] The International AI Safety Report released by the UK AISI also attempted to define and widen the scope of AI safety by including the mitigation of intentional risks, malicious uses and harms resulting from deepfake exploitation, dissemination of misinformation and adversarial attacks.[74] However, despite the initial two AI Summits at Bletchley Park and Seoul heavily focusing on the safety aspect, there was a noticeable shift and expansion of focus at the AI Summit held at Paris earlier in 2025.[75] [76] The emphasis in some jurisdictions has also gradually shifted from safety to addressing potential threats to national security,[77] including cybersecurity risks and implications from development of biological warfare.[78] Another noticeable shift in the AI discourse is the growing emphasis on driving AI innovation, with safety measures considered a roadblock by some governments in achieving global AI leadership.[79] With the nature and gravity of harms resulting from AI use compounding at exponential rates, it is crucial that AI safety receives the critical level of importance it warrants.

The Global South populations remain exposed to a distinct set of AI-related risks, ranging from fragmentation of local labour markets to the perpetuation of existing social biases.[80] [81] These vulnerabilities are further amplified by a dearth of indigenous datasets, algorithmic bias and inadequate digital infrastructure, exposing the populations to greater systemic risks often neglected by global frameworks on AI safety.[82] It becomes critical, therefore, to develop effective practices and mechanisms for risk mitigation contextualised to address the unique realities of the Global South.

Section II

AI Risk and Governance: A Lifecycle Approach

Section II of the report explores how AI safety can be operationalised through targeted interventions across the AI lifecycle, encompassing inception and planning, data collection and preparation, model design and training, verification and validation, and deployment and post-deployment. The stages of a lifecycle, and the associated risks and mitigation measures depend on the size, scale and scope of the AI system. Key safety risks are examined at each stage, such as adversarial vulnerability in the model design and training stage, and model degradation in the post deployment stage. The section also maps governance measures and notable technical interventions at each stage, including robust auditing procedures, red-teaming, and oversight mechanisms to highlight mitigation efforts and exercises. Additionally, this section highlights existing regulatory practices as part of mitigation efforts where relevant. Highlighting major considerations for the Global South underlines the research and is discussed at the end of every stage of the lifecycle. These insights for the Global South discuss emphasising equitable access, the necessity for context-specific adaptations, and inclusive and expansive training data, to prevent exacerbating regional inequalities.

Adopting a lifecycle approach allows stakeholders to study and manage the sequential progression of decisions and tasks leading up to and including the deployment of AI solutions.[83] Lifecycle management includes evaluations of the response time, quality, fairness and explainability, among others, of AI systems in context.[84] Key factors contributing to risks, namely privacy, cybersecurity, trust, interpretability, explainability, robustness, usability and wider social implications can be accounted for, and managed, given the comprehensive nature of a lifecycle approach.[85]

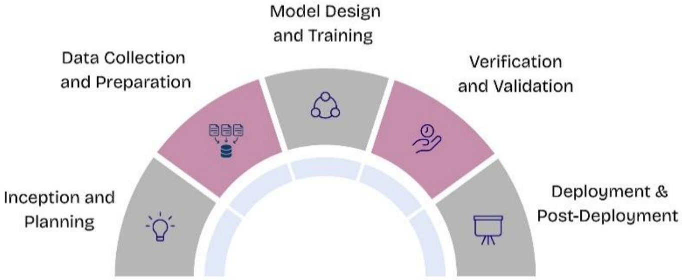

Inception and Planning
Data Collection and Preparation
Model Design and Training
Verification and Validation
Deployment & Post-Deployment

Figure 3: Stages of the AI Lifecycle

Another valuable addition of observing AI systems through this lens is the ease of identifying key actors involved across various stages, like data scientists, engineers, IT managers and compliance teams. Recognising these human parties in the lifecycle is vital to ensure appropriate allocation of responsibilities and adequate oversight of the stages, thereby supporting transparency and traceability efforts during the development and deployment.[86] Given the high number of actors involved, assigning specific roles and responsibilities is necessary for accountability, especially to address concerns during failures or breaches. By breaking down the process into a lifecycle and also identifying responsible actors, we can visualise a holistic image of the AI system in order to assess how and by whom safety is implemented. This report acknowledges the importance of key actors, but does not granularly approach risk and mitigation measures through this sole lens.

Model developers, also known as the architects, lay the foundational capabilities and conceptualise the AI system and its behaviours.[87] They build the models, crucially contributing to the potential output and its impact. System deployers are the party bridging the gap between the abilities of an AI system and its real-world application.[88] They actively customise and operationalise the system, depending on its abilities and uses within a targeted industry. Finally, the users interact with the system and uniquely introduce new information, influencing the real-world performance of the AI tool. They are most impacted by the AI system, and hence, clear explanations and directions on the performance and impact of the tool should be made available to them.

Beyond this operationalisation, two other human parties are also involved with the AI lifecycle.

Theorists are accountable for developing and advancing AI theory through a technical lens, and typically belong to academic or industrial research settings.[89] Ethicists are concerned with the principles of safe AI systems and include policymakers, commentators and critics from multiple disciplines like academia, law, journalism, economics and politics.[90] They are concerned with research beyond the technical qualities, and evaluate AI systems in light of external auditability, societal impact and wider legal compliance.[91]

Visualising the development and deployment of an AI system as an iterative lifecycle with built in testing, verification, and feedback methodologies allows for a process of continuous improvement. Distinct risks emerge at different stages of the lifecycle, necessitating tailored interventions to address them proactively. Biases and privacy violations often manifest during data collection and processing, while deception arises during model training.[92] In post-deployment, issues like unintended societal harms or jailbreaking vulnerabilities are revealed.[93] Corresponding safety measures include technical safeguards like careful data curation, adversarial robustness testing in the early stages, and governance tools such as auditing and regulatory sandboxes in the later stages. Breaking down risks and mitigation measures via stages proves useful by enabling targeted, scalable mechanisms that provide oversight, facilitate accountability and prevent compounded issues that may only manifest once the AI system is released to its context-specific users.[94] However, there are limitations to this approach. AI systems vary in their model design (foundational models as opposed to deployed applications, low-risk vs high-risk systems, etc.), which complicate generalised categorisation of stages, risks and mitigation measures.[95] Rapid technological advancements can modify these classifications further, especially given the adaptive nature of AI models. The stages overlap and are interconnected, defying neat delineations in how risks can present. This report aims to provide a broad mapping that can be referential in developing detailed and comprehensive studies as the research in this field, especially in the Global South, continues to grow.

These following two sub-sections provide a brief overview of the governance frameworks and technical safety measures related to AI safety, which we will explore in greater detail subsequently.

Governance frameworks for AI safety

Globally, various governance frameworks are being established to address and contain harms arising from the proliferation of AI. Voluntary standards, in the form of ISO/IEC 42001:2023 and the Risk Management Framework (RMF) conceived by the National Institute of Science and Technology (NIST) have proven useful in proposing mechanisms to organisations for internal governance and undertaking effective risk oversight procedures.[96] The NIST Risk Management Framework (RMF) provides a flexible mechanism for organisations involved in the development and use of AI models to identify, evaluate and effectively incorporate risk mitigation measures for harms arising through the entire lifecycle.[97] The Organisation for Economic Co-operation and Development (OECD) principles on AI also necessitate ensuring robustness, security and safety in the functioning of AI systems. These principles also recommend the creation of adequate safeguards across all the stages for prevention of unforeseen risks and unintended behaviour on the part of AI.[98]

The EU AI Act proposes a risk-based approach to AI regulation and imposes stringent requirements on developers of high-risk AI systems, which include conducting mandatory periodic risk assessments.[99] California's recently enacted AI safety legislation - the Transparency in Frontier Artificial Intelligence Act (SB 53), also implements a comprehensive governance framework by mandating transparency and disclosure requirements from developers of large frontier AI models regarding the safety framework followed by them.[100] The legislation also provides for whistleblower protections for workers of companies involved in model development and necessitates immediate reporting of a 'critical safety incident'.[101]

Technical safety measures under the realm of AI Safety

AI safety is also interpreted as a specialised domain within the ambit of system safety engineering, which enables investigating and offering solutions to AI-generated social and ethical harms through the application of foundational safety engineering principles.[102] Safety engineering prescribes taking a 'safety-by-design' approach at the outset, enabling better risk management and avoiding retrofitting safeguards until after the risk becomes apparent post the model deployment.[103] Designing technical safety measures, therefore, forms an integral part of ensuring the safety of AI systems and withstanding adversarial attacks in the form of data poisoning, jailbreaks and prompt injections.[104] Enhancing system safety also necessitates considering the behaviour of the numerous components of the AI system working in unison. This can facilitate crafting interventions throughout the system lifecycle in the broader context of its functioning and the environment under which it operates.[105] Dissecting the different stages of the AI lifecycle can also prove valuable in designing effective mitigation strategies to contain the downstream risks associated with AI implementation. A multitude of safety techniques including employing anomaly detection and adversarial robustness (such as red teaming) to ascertain malicious use[106] have been developed to minimise the risks arising out of the various stages of the AI lifecycle, which shall be dealt with subsequently.

A. Inception and Planning

The inception and planning stage is the earliest stage of the AI lifecycle. This stage involves context setting, identifying objectives and purposes that involves defining use and constraints or perceiving risks such as identifying affected communities. These tasks are critical for assessing feasibility and foreseeable misuses, and setting the accountability, oversight, and risk-management structures that will guide the entire lifecycle.[107] This stage is closely tied to NIST's AI RMF "Govern" and "Map" functions. The "Govern" function relates to outlining processes for the AI lifecycle to identify and account for foreseeable risks that may arise. This function involves steps such as documenting legal requirements and establishing accountability structures.[108] The "Govern" function is supported by the "Map" function which provides further context on the outlining of the AI lifecycle through steps such as mapping impacts for individuals, groups, communities and society.[109] The inception stage plays a critical role in determining and accounting for an AI system's long-term safety and social impacts because it defines the trajectory of the system.

i. Identified Risks

During the inception and planning stage, AI safety risks may emerge when problem definitions, objectives, potential risks and contextual parameters are insufficiently examined and articulated.[110] The absence of meaningful engagement with relevant stakeholders and affected communities further compounds these risks by obscuring local concerns, domain constraints, and lived-experience insights.[111] Early risks also stem from incomplete anticipation of failure modes,[112] security threats, and downstream impacts on individuals, groups, and institutions.[113]

ii. Governance Measures

These challenges can be addressed through rigorous purpose-and context-definition practices, structured stakeholder and community consultation, systematic early-stage risk identification, threat modelling and impact assessment processes, and clear allocation of governance roles and accountability mechanisms. It is relevant to note that while frameworks often recommend some of these mechanisms to be carried out across the AI lifecycle, it is critical that they are employed at the outset to prevent irreversible safety harms at later stages.[114]

Some of the key governance mechanisms under the inception and planning stage include purpose specification and context definition mechanisms, structured stakeholder and community engagement, early risk identification, and governance and accountability allocation.

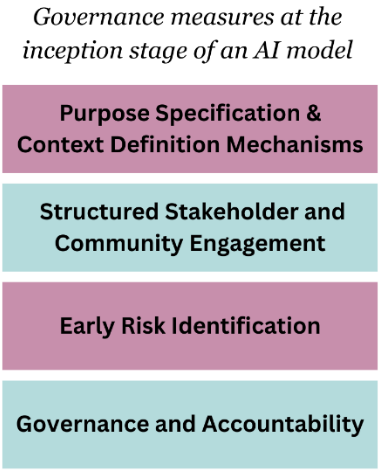

Governance measures at the inception stage of an AI model
Purpose Specification & Context Definition Mechanisms
Structured Stakeholder and Community Engagement
Early Risk Identification
Governance and Accountability

Figure 4: Inception Stage of AI Model: Governance measures

Purpose Specification and Context Definition Mechanisms

It is imperative to outline the purpose and set the context at the beginning of the AI lifecycle. This includes delineating and defining the AI system's purpose, intended use, non-intended uses, operational context, and constraints before development begins.[115] Doing so is relevant because several challenges, particularly at the design and training stage and at deployment, arise from misalignment between the objectives of the AI systems and the priorities of the designer, discussed in subsequent sections.

The 'Map' Function within the NIST AI RMF recognises the need to outline and define the purpose and context of the AI system, by specifying the environmental, organisational, and functional conditions that shape how risks arising from the AI system should be understood. These conditions relate to practices like documenting the organisation's mission and relevant goals,[116] intended purposes, anticipated beneficial use cases. It can also relate to contextual parameters relevant while deploying an AI system, like norms, and legal frameworks.[117]

Structured Stakeholder and Community Engagement

Through this mechanism, AI developers and deployers must establish formal processes to engage with diverse stakeholders in consultative processes. These stakeholders may include users, workers, citizens, domain experts, academics, civil society, grassroots organisations and marginalised communities who will also be impacted by the use of AI or whose data has been used to train models. Early engagement reduces downstream fairness risks, misalignment with societal values, and contextual misalignment.[118]

Identification and engagement with stakeholders is an integral aspect of the 'Map' function under the NIST AI RMF.[119] This framework articulates how engagement with relevant stakeholders and communication towards shared understanding can support AI developers and deployers in understanding the likelihood and magnitude of potential impact.[120]

Early Risk Identification

Organisations must identify risks and impacts that may potentially arise from the AI system through threat modelling and impact assessments. While it is critical to evaluate the system for potential risks throughout the lifecycle, it is particularly imperative for these assessments to be conducted at a foundational stage.

For instance, the 'Map' and 'Manage' functions of the NIST AI RMF explicitly require early identification of foreseeable misuse and safety risks.[121] Similarly, the EU AI Act requires risk management systems to be established and maintained for high-risk AI systems.[122] These systems comprise both risk assessment as well as risk management. Risk assessment may be carried out at the inception and planning stage. However, under the EU AI Act, the risks articulated correspond to those which may be mitigated during the development or design stage, or "when adequate technical information is provided."[123] As a result, this report discusses the operationalisation of the risk management system under the EU AI Act under the model design and training stage.

The EU AI Act stipulates the steps involved in the implementation of the risk management system to include identifying and analysing risks which may either be known or reasonably foreseen, particularly in terms of impact on health, safety, or fundamental rights.[124] The Guidance for Risk Management of Artificial Intelligence systems ("Guidance") specifies that risk identification includes identifying the sources of risk, and potential areas which the deployment of the AI system may impact, in order to create a comprehensive risk register.[125] The Guidance states that risk analysis involves examining the nature, sources, likelihood, and potential consequences of the identified risks.[126]

Subsequently, the AI Act requires that these risks are to be estimated and evaluated[127] prior to adopting appropriate and targeted risk management measures to mitigate the risks identified above for this stage.[128] The Guidance states that risk evaluation involves comparing the identified risks with the risk criteria, risk appetite and tolerance to determine whether an identified risk is acceptable.[129]

Governance and Accountability Allocation

This process involves defining and allocating clear roles for stakeholders involved across the AI lifecycle, including the AI owner, deployers, project manager, risk officer, human-oversight authorities, etc. This is significant because systemic risk often occurs due to failures and ambiguity in accountability. When stakeholders are unclear about the responsibility allocated to them, this can give rise to unsafe decision-making, governance bottlenecks, and organisational blind spots.[130]

This has been recognised by the EU AI Act, which details the obligations which must be allocated among providers,[131] deployers,[132] importers,[133] distributors[134] and other stakeholders. While it is not necessary to fulfil all the obligations at the inception stage, it is critical to document and make the relevant stakeholders aware of their corresponding responsibilities at this stage to prevent safety harms arising subsequently.

Similarly, the 'Govern' function under the NIST AI RMF emphasises early allocation of accountability structures within AI systems.[135] This includes practices like establishing, documenting and communicating clear, well-defined roles, responsibilities, and communication pathways relating to mapping, measuring, and managing AI risks, in order to support the systematic identification, assessment, and mitigation of AI-related risks.[136]

iii. Considerations for the Global South

Multinational companies typically operate out of multiple and diverse social contexts, which can present distinct challenges in how they strategise in terms of critical decisions. This is particularly relevant for markets with "cultural distance," where there is a difference in terms of cultural values. In such instances, there is often greater transfer of practices from the "home country", which in most cases relates to the Global North.[137] This can often result in limited incentives for some of the biggest global foundational model developers and deployers in key sectors such as health, recruitment and education towards investing in understanding local languages, cultural contexts, demographies, and power structures in non-priority markets in the Global South. Consequently, this may result in an underrepresentation of diverse needs. For instance, techno-linguistic bias favouring dominant languages from the Global North being prioritised in a manner that hinders AI systems from being able to correctly represent concepts from other communities.[138]

Often, due to the above factors, there is limited participation of users from the Global South and marginalised communities within these jurisdictions in developing and co-designing AI models at the inception stage.[139] It is also critical to take into account the dominance of AI players established in the Global North in developing AI infrastructure, and its implications on data sovereignty,[140] individual privacy and communities' rights over their cultural and linguistic resources.[141] This hegemony also risks technological dependency of the Global South on the Global North, a loss of local autonomy, and may overlook local needs, languages, and social norms in the inception and planning of AI systems.[142]

These challenges are also often likely to be exacerbated due to several Global South jurisdictions lacking effective governance frameworks such as data protection and AI safety regulations and industry standards.[143]

B. Data Collection and Preparation

Data collection is the stage of the AI lifecycle where raw data is acquired for training, validating, and testing an AI model.[144] Data collection can involve data acquisition, where new datasets may be discovered or generated. Data discovery involves extrapolating insights from existing datasets by identifying patterns and trends in data, which can improve security and inform decision-making.[145] Data generation refers to the process where synthetic data is artificially generated through computer simulations or generative models to supplement "real-world data" in a cost-effective manner.[146]

Data preparation is the stage of the AI lifecycle where the raw data is processed and refined before further stages.[147] This process involves improving upon or augmenting datasets or making them more representative by improving the quality of existing data to be more consistent, accurate and reliable.[148] The quality of datasets is often improved by handling missing data or values[149] or providing additional context to raw data through data labelling and annotation.[150]

Datasets may also be made more representative by ensuring diversity of data, either by replacing existing data that may cause bias,[151] or increasing representation of underrepresented data samples in datasets.[152]

i. Identified Risks

Several risks can arise at the data collection and preparation stage.

Transparency and explainability

A significant risk that may arise is a lack of transparency and explainability for users and deployers.[153] This is due to limited documentation of how processes in the data collection and preparation stage are employed. These processes include techniques such as data augmentation (where the size of the dataset is increased using synthetically generated data), and data repurposing (where data collected for a certain purpose is reused to train AI models to identify patterns for a different purpose).[154] These limitations in transparency may also contribute to challenges for users and deployers in identifying threats relating to adversarial manipulation,[155] which presents challenges in terms of determining accountability for harms stemming from a model's outputs.[156] Moreover, a lack of transparency due to limited documentation of the sources and nature of data collection may also give rise to certain concerns. This may be due to the quality of data collected and used for the AI model being 'bad.' For instance, misinformation detection tools developed using datasets drawing upon misinformation and disinformation present on the Internet, may be less accurate. This is because these tools may assume the misinformation they are trained on to be true.[157] In certain cases, there is also the risk of the nature of data collection being bad, as opposed to the data itself; for instance, where data has been scraped in an unauthorised manner by web crawlers.[158]

Data privacy violations

There may also be concerns of data privacy violations. These may arise in the absence of informed consent, and limited adherence to data protection principles.[159]

Bias

AI models may sometimes exhibit biased behaviours and produce inequitable and unfair outcomes. One form of such bias could be statistical bias, which can arise due to particular demographic groups being underrepresented in training datasets.[160] For instance, demographic underrepresentation in datasets used for computer vision models can produce higher error rates for darker-skinned individuals as compared to lighter-skinned individuals.[161] Limited obligations for explainability and transparency on prominent AI systems with regard to information on datasets can also result in users being unaware of the implications of potential biases.[162]

Another form of bias could include societal bias, relating to structural inequalities in society, which are reflected through the data that has been collected. For instance, predictive AI models which have been trained to identify and reproduce existing patterns in datasets may replicate prevalent societal bias surrounding male and female representation in different fields like medicine, engineering, etc.[163]

Risks in data labelling

Data labelling processes can often give rise to fairness risks. Data labelling refers to identifying and providing context to raw data, such as images and videos for a machine learning model.[164] This process can often fail to account for complexities in data. For instance, emotion recognition systems can create overly simplistic representations of complex humans, failing to capture local contexts of expressing emotions, and other situational nuances.[165] This could consequently produce unfair outcomes where an individual is incorrectly profiled for mental health concerns, for instance.[166]

Additionally, data labelling may also present risks in allocative decisions due to underrepresentation of data, or can reinforce societal biases due to misrepresentation in labels. For instance, the UK ICO illustrates how common practices like uniform sampling from the training dataset, may result in unfairness for underrepresented communities. This is because uniform sampling, where a data point is randomly selected from a dataset, is less likely to present a data point of an underrepresented community, simply due to less data being available about that community.[167]

ii. Governance Measures

The above identified risks are fundamentally tied to the data that models are trained on,[168] and certain governance measures like record keeping and audits can be effective in accounting for these risks at the data collection and preparation stage.

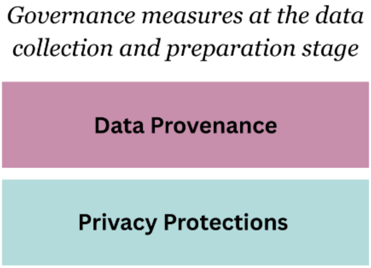

Governance measures at the data collection and preparation stage
Data Provenance
Privacy Protections

Figure 5: Collection and Preparation Stage of AI Model: Governance Measures

Data Provenance

Data provenance refers to the detailed record of the origin, history, and transformation of data inputted at the data collection stage.[169] This mechanism helps ensure that the data used to train or test AI systems is traceable and trustworthy - for instance, by verifying the data collected, the creators of the data, and records and histories of how the data has been modified. This can consequently help verify the authenticity and consent associated with the data.[170]

There are several mechanisms and technical measures through which data provenance can be operationalised. This includes auditable chains, which identify the origin, owner, validation, change points, and destination within the dataset. Some of the key artefacts underpinning these auditable chains include a registry of sources, end-to-end maps tracing data touchpoints from its origin across various processes and transformations, and detailed logs mapping outcomes to responsible decision-makers.[171] In the absence of uniform and universally accepted standards or frameworks for data provenance, several researchers have also proposed documentation standards like datasheets,[172] data statements,[173] and data cards.[174]

Regulatory provisions can also support AI model developers in adhering to principles of transparency, robustness and fairness through data provenance. For instance, the EU AI Act requires providers of general-purpose AI models to develop a "sufficiently detailed" summary of the data used to train the AI model. This summary must be in accordance with a template provided by the AI Office, and must be made publicly available.[175]

NIST AI Risk Management Framework 1.0 also underscored documentation, traceability, and data provenance as integral to trustworthy AI. Within its 'Map' and 'Govern' functions, the framework calls for systematic recording of information related to data collection, selection, system design, and testing. This documentation is intended to enable accountability, transparency, and oversight throughout the AI system lifecycle, including the data collection stage.[176]

Canada's Voluntary Code of Conduct on the Responsible Development and Management of Advanced Generative AI Systems calls on model developers to publish training data descriptions. This includes data about the types of training data used to develop the AI system, as well as risk identification and mitigation measures.[177]

Moreover, a Checklist for AI Auditing, commissioned by the EU Data Protection Board, also recommended certain factors that could be accounted for while the training data is being audited.[178] This could include examining whether data sources have been documented, and whether input data sets, data use and intermediate data, and output data can be traced.[179]

Privacy Protections

Data provenance is a significant governance mechanism to support accountability and transparency within the data collection and preparation stage. However, it is imperative that such data provenance, as well as data collection and preparation more broadly, be done in accordance with data protection frameworks.

For instance, the General Data Protection Regulation[180] [181] [182] [183] [184] - the provision specifically articulates that producers should be encouraged to account for data protection rights while developing products and services which process personal data.

The Guidelines on the interplay between the EU Data Protection Regulation and the Artificial Intelligence Act[185] are slated to be released in 2026, according to the European Data Protection Supervisor.[186] However, literature already points to the existing impact of the GDPR on AI systems, including the significance of principles like data minimisation.[187] A study by the Panel for the Future of Science and Technology submitted to the European Parliament contended that AI systems can integrate data processing requirements and safeguards established by the GDPR.[188]

The study reiterated the need for mechanisms such as pseudonymisation with respect to data collected for developing the AI systems. The study also recommended identifying distinctions between the use of personal data for the purpose of developing a training dataset for AI systems, which involves broader correlations amongst individuals, as compared to personal data being used to profile and make decisions about individuals.[189] This can support the principle of purpose limitation provided under the GDPR by limiting data processing to the purpose for which it may have been collected. The study also recommended establishing deterrents against institutions that intentionally disregard the interests of data subjects and thereby exploit their trust.[190]

Research also points to consent registration as a technical measure that provides clarity regarding whether creators have consented to the collection and storage of data, and also allows people to grant, withdraw, or negotiate consent.[191]

The Checklist for AI Auditing, commissioned by the EU Data Protection Board, also recommended ascertaining whether data sources and the method of collection contravene data protection principles under the GDPR.[192] The recommendations also propose audits to examine whether the process of data collection followed the approach of privacy by design, as laid down under the data protection principles under the GDPR.[193]

Data governance and management best practices towards Fairness and Bias Mitigation

The EU AI Act requires that training, validation and testing data sets shall be relevant, sufficiently representative, and account for geographical and contextual characteristics.[194]

The UK Information Commissioner's Office ("UK ICO") provides implementational direction for this provision through its guidance on ensuring dataset fairness, which specifies certain factors to be considered and demonstrated to ensure the AI system is trained and tested on datasets that are representative, relevant, accurate, and generalisable.[195] These factors include designing datasets to be representative of relevant populations and communities by collecting sufficient data (both in terms of quantity and quality).[196] The guidance also acknowledges the significance of reliability and impartiality in data collection within the above factors by recommending that data be assessed, recorded and sourced through "sound collection methods" in an up-to-date and accurate manner.[197]

The UK ICO takes into consideration the various sources of bias in datasets and AI systems (including data collected through third parties).

Bias from external datasets

The UK ICO emphasises the need to assess risks of bias particularly when organisations procure datasets from other organisations through processes like data sharing.[198] For instance, the UK ICO highlights how selection biases in sampling and measurement may arise when non-representative external datasets are integrated with data collected directly by organisations themselves.[199]

Bias mitigation in data labelling/annotation

Harms can arise from misrepresentation or underrepresentation of certain data points in data labelling and annotation. This can be mitigated by implicit bias training to equip AI companies with an understanding of how underrepresentation and misrepresentation may impact the decision-making of the AI system. Participatory design through inclusion of underrepresented communities in the labelling process can be useful in helping organisations formulate inclusive labelling criteria and protocols.[200] For instance, the Uli dataset for automated detection of hate speech and gendered abuse in Hindi, Tamil and Indian English employs a participatory approach by selecting annotators who identify as women or members of the LGBTQIA+ community in South Asia.[201]

Bias mitigation through dataset modification

Bias mitigation at the pre-processing stage can also involve modifying datasets to either remove data that may result in biased outcomes and discrimination, or correct an imbalanced dataset by increasing representation of communities that were previously underrepresented.[202]

During the data collection process, every data point assumes an equal weight, which can lead to marginalised communities remaining underrepresented in datasets as well.[203] One way to address aggregation bias that may arise due to certain groups being underrepresented includes reweighting data points during data preparation to balance the representation. For instance, data was reweighted to avoid unfair outcomes in a clinical prediction model for postpartum depression (PPD). The model had been trained on potentially biased data and was diagnosing higher numbers of white women with PPD, contrary to medical literature pointing to evidence of higher prevalence of PPD among women from marginalised communities. In this case, reweighting data mitigated bias by reducing the effect of the biased data point (such as race) in prediction by removing it as a characteristic.[204]

Similarly, during the data preparation process, data labelling can often fail to account for structural and societal challenges and can perpetuate bias and discrimination.[205] These structural inequalities can be accounted for by changing data labels, wherein labels can be modified on the basis of algorithmic fairness metrics to mitigate risk against communities most vulnerable to such discrimination.[206]

Other bias mitigation strategies can include mechanisms such as data visualisations, which chart changes in training data's distribution patterns to indicate potential bias within the corresponding dataset.[207]

iii. Considerations for the Global South

Some of the risks identified in this stage may pose specific challenges when an AI system is developed or deployed in the Global South. Obtaining informed consent in data collection can often be a challenge due to linguistic diversity impeding the accessibility of transparency and explainability disclosures for individuals whose data is being collected.[208]

A study on low-resource government health systems in Zanzibar provides insights into how several patients were unaware about the individuals accessing their data or why it was being collected.[209] These issues arose primarily due to challenges in drafting data access management guidelines and translating policies into Swahili.[210] In any case, it is also pertinent to note that consent for data collection for AI systems in the Global South cannot be regarded to be fully meaningful due to power asymmetries between powerful multinational corporations and users in the Global South.[211]

Separately, in the course of our interactions with stakeholders, they highlighted methodologies and taxonomies under data justice initiatives such as SoberanIA, which may necessitate Big Tech companies having to pay license fees for using indigenous languages in the future fees.[212] Linguistic diversity can also pose challenges with respect to data preparation due to certain preprocessing methods being biased towards English.[213] Researchers have also identified how existing preprocessing methods such as tokenisation, normalisation, and embedding are biased towards English or other high-resource languages, leading to systematic errors.[214]

There are also challenges relating to traceability at the data collection and preparation stage, due to standards and methods of data collection not being uniform.[215] Non-standard data sources like paper records, verbal reports, and informal data, which may be more commonly used in the Global South,[216] may have higher measurement errors, inconsistent formats, and missing fields.[217] Moreover, case studies from the usage of a Nigerian health chat have revealed how a lack of traceability and explainability in sampling and weighting can lead to opacity and hinder transparency with respect to representation of communities while developing AI models.[218]

C. Model Design and Training

The model design stage includes selecting model algorithms, defining model architecture, and training techniques to address the objectives and problem statement identified at the inception stage.[219]

Subsequently, in the model training stage, the model is subjected to the data which was collected and prepared in the data preparation stage.[220] Thereafter, the model learns to recognise patterns within this data, which influences its capacity to generate outputs such as predictions or decisions. Appropriate training algorithms (which were selected during the model design stage), such as supervised, unsupervised learning, or reinforcement learning,[221] are applied and implemented for this purpose.[222]

i. Identified Risks

Misinformation

Certain AI systems, like LLMs, are designed to have the capability to generate synthetic media which is virtually indistinguishable from human-generated content. This can pose risks of misinformation and enable deception, fraud and impersonation.[223] These risks can arise when users are unaware they are interacting with AI chatbots, particularly in critical sectors such as finance and healthcare.[224] The usage of AI to generate "deepfakes" can also be misused by bad actors to create sexually explicit content,[225] impersonate celebrities,[226] carry out fraudulent activities such as identity theft and financial scams,[227] or even to influence electoral outcomes.[228] Misinformation is an indirect risk in the model design stage because this outcome is dependent on how AI systems are designed and safety measures for transparency of users are taken, as discussed subsequently.

Fairness and bias risks

In the data collection stage, the bias often occurs due to the training data being underrepresentative.[229] On the other hand, bias in the model training stage often occurs due to inherent biases in the algorithms used to train the machine learning model. These inherent biases refer to biased algorithm design, where debiasing techniques such as reweighting (where data is adjusted to be more representative) can remain ineffective due to biased assumptions by designers.[230] For instance, in an attempt to mitigate gender-based bias in hiring decisions, designers may fail to account for race-based bias within a gender that has been traditionally underrepresented.[231] These biases are subsequently reflected in the outputs produced by the AI system.[232] For instance, in the previous example, the AI system may subsequently prioritise white women in its hiring decisions over Black women.

Adversarial Vulnerabilities:

Adversarial evasion attacks occur when carefully designed, often imperceptible perturbations, known as adversarial examples, are introduced into an input by sophisticated attackers. This causes machine-learning models to produce highly inaccurate or otherwise arbitrary predictions, despite the input appearing unchanged to humans during oversight.[233] These attacks can undermine trustworthiness, particularly in high-risk AI systems like autonomous vehicles and critical infrastructure, where adversarial failures can have severe implications for AI safety.[234] For instance, a stop sign may be manipulated by adding imperceptible noise to the image, which may hinder an AI system from recognising the image as a stop sign.[235]

***Prompt Injections*:**

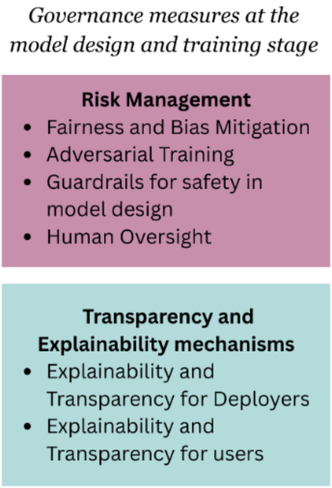
This refers to instances where bad actors, such as hackers, exploit large language models with malicious inputs disguised as legitimate prompts to produce outcomes containing misinformation, sensitive information, or information that contravenes human ethics.[236] For instance, in early versions of ChatGPT, users were able to craft prompts (such as under the guise of pretence) that enabled ChatGPT to produce concerning outputs such as racist and homophobic content.[237]

Misalignment:

This refers to instances where the AI model learns an indirect pattern, which differs from the human intent and the objectives outlined during inception.[238] Misalignment can give rise to unfavourable and unpredictable outcomes at the deployment stage.[239] For instance, social media recommender systems that have been trained to increase user engagement may prioritise political misinformation.[240]

ii. Governance Measures

Certain governance measures such as risk management and transparency mechanisms can be effective in accounting for these risks at the model design and training stage.



Governance measures at the model design and training stage

Risk Management

- Fairness and Bias Mitigation
- Adversarial Training
- Guardrails for safety in model design
- Human Oversight

Transparency and Explainability mechanisms

- Explainability and Transparency for Deployers
- Explainability and Transparency for users

Figure 6: Model Design and Training Stage of an AI Model: Governance Measures

Risk Management

The risk management system under the EU AI Act, discussed in the inception stage, is understood as a continuous iterative process across the AI lifecycle. While identification and evaluation take place at the inception stage, the techniques for risk management and mitigation are operationalised during model design and training. Although the EU AI Act does not stipulate any specific risk mitigation techniques, risk management techniques can include fairness and bias mitigation, adversarial training, safety guardrails, and human oversight.

- ***Fairness and Bias Mitigation:*** Bias mitigation may be implemented differently across the design and the training stage. With regard to the design stage, the AI Act requires that high-risk AI systems that continue to learn after market placement or first use, be developed in a manner that prevents bias arising due to feedback loops.[241] This may present itself as instances where biased outputs may be perpetuated as inputs for future iterations of the AI system.[242] For instance, AI systems trained on biased data may perpetuate biased hiring decisions, continuing to underrepresent marginalised communities. This could reinforce existing biases and inform biased datasets in the future, to be subsequently used to make hiring decisions.

  With respect to the training stage, bias and unfairness mitigation techniques involve in-processing methods. In-processing methods can often account for challenges of bias amplification that occur during the model training stage, where bias occurs due to unfair algorithms, irrespective of the representative nature of the dataset.[243] For instance, a study revealed that an algorithm over relied on past healthcare costs to predict future medical care needs, resulting in white patients being prioritised. This bias arose because the algorithm made an incorrect inference from data, failing to account for the fact that Black patients with similar health conditions as white patients were incurring lower healthcare costs due to socio-economic and access barriers.[244]

These in-processing methods often include fairness constraints and adversarial debiasing.

Fairness constraints refer to formal requirements or rules which are introduced during the training process to mitigate biases that may arise when AI predictions are correlated with sensitive attributes such as race or gender.[245]

Adversarial debiasing promotes fairness by training the primary AI model in opposition with an adversarial network (a secondary model that attempts to detect weaknesses, biases in the primary model) to reduce the influence of sensitive features.[246]

- ***Adversarial Training:*** Adversarial training involves training an AI system to improve robustness against adversarial attacks by training the model on a combination of inputs which are both clean as well as examples of adversarial perturbations.[247] As demonstrated in the risks above, adversarial perturbations refer to inputs that have been deliberately modified to produce unfavourable outcomes. Under this approach, AI systems improve robustness by learning how to accurately classify and differentiate between clean and perturbed inputs.[248]

The NIST AI 100-2 (2025) report on Adversarial Machine Learning provides detailed guidance on adversarial training, certified robustness techniques, and threat models tailored to different attack surfaces.[249]

Regulatory provisions also recognise the need for mitigation strategies for improving robustness against adversarial risks. For instance, the EU AI Act stipulates that high-risk AI systems must be designed and developed with appropriate robustness, cybersecurity, and resilience.[250] The provision specifies that security measures must include protection against adversarial inputs, confidentiality attacks, model flaws, and unauthorised alterations to datasets or pre-trained components through data poisoning and model poisoning.[251]

- ***Guardrails for safety in model design:*** The EU AI Act recommends taking technical and organisational measures to achieve robustness of high-risk AI systems against errors, faults or inconsistencies occurring within the AI system's operating environment.[252] These can include technical redundancy solutions, such as backup or fail-safe plans,[253] where multiple AI models run parallelly, allowing a model to ensure continuity or supervision in the event of another model failing or behaving unpredictably.[254]

  For instance, utilising two models, the primary model's outputs can be monitored for unsafe or misaligned behaviour, especially under adversarial queries. Under this approach of Two-Tier or Guardian-Based Models, a secondary or "guardian" model supervises the primary model.[255]

- ***Human Oversight:*** Human oversight refers to the ability of humans to exercise agency to monitor, intervene or override decisions made by AI systems.[256] Frameworks such as the OECD AI Principles acknowledge the potential of AI to negatively impact human rights and democratic values[257] (which may occur, for instance, due to misinformation and bias). This framework therefore recommended human agency and oversight as a safeguard against these risks.[258] Similarly, the United Nations Educational, Scientific and Cultural Organization (UNESCO) Recommendation on the Ethics of Artificial Intelligence proposes human oversight, for the purposes of ensuring both responsibility and accountability. The framework suggests that jurisdictions should seek to ensure that responsibility across the AI lifecycle can be attributed to specific physical persons or existing legal [259]☐

  The EU AI Act reiterates this need for human oversight, and embeds human oversight as an overarching governance mechanism across the AI lifecycle with specific ways corresponding to the model design and training stage, which are discussed subsequently.[260] The EU AI Act seeks to mitigate risks that may arise to health, safety or fundamental rights during the use or misuse of high-risk AI systems.[261] The EU AI Act specifies that high-risk AI systems be designed and developed in a manner allowing oversight by natural persons during deployment.[262] Under this provision, the natural persons assigned to carry out human oversight activities for this purpose must be equipped with the capacity to accurately interpret the merits and limitations of the relevant high-risk AI system.[263]

Researchers have noted that while Article 14 of the EU AI Act is a significant development towards human-centric AI, the provision does not provide specific guidance on the modes through which human oversight is to be operationalised.[264] Instead, the provision requires that oversight measures be proportionate to the potential risks, intended level of autonomy and context of deployment of the high-risk AI system.[265] This approach allows different sectors to contextualise human oversight measures to the needs of their sectors while maintaining accountability.[266]

The sub-guideline on Human autonomy and Oversight under the Inter-Parliamentary Union's Guidelines on Ethical Principles for AI Use in Parliaments recognises three primary modes of human oversight in AI.[267]

These include Human-in-the-loop (HITL), Human-on-the-loop (HOTL), and Human-in-command (HIC). Each of these modes corresponds to different levels of human intervention and autonomy of the AI system.[268] The HITL model involves human mediation of all decisions taken by an AI system. The HOTL model employs a balance between human oversight and AI autonomy wherein human intervention may be carried out during the project development phase, shifting to human monitoring of AI decisions and outputs during the operational phase. Through the HIC model, a more in-depth analysis of the implications of an AI system can be undertaken, supported by public feedback regarding the AI system.[269]

However, only the HITL mode comes into place during the design and training stage,[270] while the other two modes come into place primarily post training. The HITL mode of human oversight includes supervised learning, reinforcement learning from human feedback (RLHF) and active learning. HITL in supervised learning involves training AI models through labelled datasets which have been annotated by human data scientists (for instance, human labelling of text as “spam”).[271] Reinforcement learning refers to training an AI model through its interactions with its environment, and RLHF is a type of reinforcement learning where the AI model is trained with direct human feedback through reward functions.[272] In the case of active learning, human input is only sought for categories of predictions where the AI model presents lower confidence.[273]

Transparency and Explainability mechanisms

Explainable AI refers to processes and mechanisms providing human users with an understanding of the expected impact and potential risks and biases associated with an AI model.[274] Transparency is a key aspect of explainability,[275] and it can be embedded into the model design and training stage in a manner that allows both the deployers as well as the users to more meaningfully understand the AI system and its outputs.[276]

- **Explainability and Transparency for Deployers:** The EU AI Act acknowledges the need for transparency during the design and development of AI systems and lays down certain transparency requirements. For instance, the EU AI Act requires high-risk AI systems to be designed in a way that "its operation is sufficiently transparent" that allows deployers to appropriately use and interpret outputs generated by the AI system.[277] This includes providing documentation relating to the intended purpose, accuracy level, robustness, and potential risks of the AI system. Instructions for use should also specify human oversight measures, computational and hardware requirements, maintenance needs, and logging mechanisms which facilitate appropriate functionality.[278]

- **Explainability and Transparency for users:** Recent research has highlighted the need for explainable AI, which would ensure that users interacting with AI systems are able to understand its outcomes and decisions.[279] Explainability supports users in understanding, verifying, and ascribing accountability to decisions made by AI systems, facilitating greater transparency and trustworthiness for users.[280] For instance, it can help users understand any biases that may exist in the AI system and its impact on hiring decisions made with regard to a user.[281]

  More recently, research has acknowledged the need for "human-centred explainable AI,"[282] and supporting non-technical users in understanding AI systems and their outcomes or decisions.[283] Some of the mechanisms to operationalise such explainability for non-technical users include participatory design and non-conventional explainability techniques. For instance, research has underscored the significance of participatory and co-design practices in promoting accountability for the deployment of machine-learning interventions implemented in the context of local communities.[284] Similarly, participatory design practices can be leveraged towards collaboration between scientists and local communities for the purpose of co-designing AI systems towards more explainable systems.[285]

Moreover, the EU AI Act embeds transparency into the design stage by mandating transparency for users of the AI system, to prevent risks of impersonation and deception.[286] The EU AI Act places transparency obligations both with respect to interaction with AI systems, as well as engagement with outputs synthetically generated by the AI system.

For instance, the EU AI Act requires providers to ensure that AI systems designed to interact with natural persons are designed and developed to ensure that users are made aware of the fact that they are interacting with an AI system,[287] particularly in the deployment of emotion recognition systems or biometric categorisations.[288] Similarly, regulatory frameworks in the US also require the embedding of such transparency during deployment. For instance, California's law regulating AI companion chatbots requires platforms to explicitly inform child users that conversations are AI-generated.[289] Prior to this, the Utah Artificial Intelligence Policy Act was enacted, requiring entities to disclose to consumers in a clear and conspicuous manner that they were interacting with generative AI entities, and not humans.[290]

The EU AI Act also requires that AI providers mark synthetic output (such as text, audio, images and videos) generated by AI systems as artificially generated or manipulated.[291] This includes use cases where the AI system is deployed to generate content which constitutes a deep fake,[292] or to generate or manipulate text published in relation to matters of public interest.[293] Similarly, the Indian government released draft amendments to the Information Technology (Intermediary Guidelines and Digital Media Ethics Code) Rules, 2021 ("IT Rules, 2021"), requiring Gen-AI and social media platforms to label 'synthetic information.'[294] It is important to note however, that there are concerns with watermarking and traceability, particularly privacy concerns surrounding the misuse of users' personal data in the absence of adequate safeguards.[295]

These requirements effectively become operative at the deployment stage when the AI provider makes the AI system available for use.[296] However, the First Draft Code of Practice on Transparency of AI-Generated Content ("Draft Code of Practice") published by the European Commission ("EC") suggests that certain mechanisms such as watermarking may be embedded at the training stage itself.[297]

Moreover, it is also imperative for AI systems to be designed in a manner to allow for compliance with transparency obligations at the deployment stage. The EC is currently developing Guidelines and a Code of Practice on Transparent AI systems to provide clarity on technical implementation means for operationalising Article 50.[298]

Once released, these technical implementation mechanisms can be embedded to adhere to transparency requirements at the model design and training stage. In this manner, transparency to the user in terms of notifying them when they are interacting with AI systems or AI-generated outputs, may help mitigate risks arising from deception and impersonation facilitated by interactions with AI systems.

iii. Considerations for the Global South

While AI systems are increasingly being deployed in Global South countries, technical governance mechanisms for AI safety deployed in these jurisdictions often fail to take local contexts into account.[299]

For instance, there are certain constraints with respect to adversarial robustness. Research has identified that developing adversarial robustness requires more training data.[300] This can have implications for marginalised communities in the Global South whose data may be underrepresented in datasets.[301] For instance, our expert stakeholders reiterated the challenge of limited existing digital data in the Global South. They highlighted the work of projects such as Masakhane in Africa which are working on creating datasets to increase access to low-resource African languages.[302] They also highlighted the need for the Global South to focus on curating higher quality datasets with less data in order to prioritise quality of data over quantity, the latter of which is currently limited.

Moreover, certain challenges in relation to human oversight also present themselves. Jurisdictions in the Global South have recently been recognising the need for human oversight as a governance mechanism to mitigate safety risks in the AI lifecycle. The recently released India AI Governance Guidelines also include human oversight as a safeguard to account for risks stemming from loss of control in sensitive sectors, within their People-First Approach under their Key Principles.[303] However, it is also imperative to consider the limitations of human oversight and not over-rely on this mechanism for AI safety.[304]

The India AI Governance Guidelines acknowledge the limitations of human oversight from a sectoral perspective (with respect to high-velocity sectors where direct human oversight may not be effective).[305] However, research on Article 14 of the EU AI Act points to broader challenges with human oversight, like humans' cognitive constraints, and how automation bias can pose constraints to the efficacy of the provision.[306] These concerns are particularly relevant considerations for the Global South as well. This is because the AI ecosystem in certain jurisdictions within the Global South faces significant constraints with respect to limited technical knowledge and experience operating AI tools.[307] This may present challenges with human-in-the-loop models currently envisioned.

It is also crucial to consider the concept of "explainability pitfalls."[308] Researchers contend that irrespective of explainability, users may disregard independent judgment and subordinate their decision-making to AI systems.[309] This is particularly relevant because studies have pointed to the heightened trust users in Global South jurisdictions such as China, Brazil and India have for algorithmic decisions and AI systems.[310] While this ties to the arguments of automation bias discussed by Fink, this heightened trust could also mean that transparency obligations such as those under Article 50 of the EU AI Act, requiring providers to indicate to the user that they are interacting with an AI system like a chatbot, may not be sufficient approaches for AI safety.

D. Verification and Validation:

The vocabulary of 'verification and validation' (henceforth, "V&V") of AI systems can be traced back to the need to ensure pre-deployment accuracy of the system. V&V represents both a pre-deployment procedural stage and ongoing operationalisation of technical measures throughout the AI lifecycle, focused on evaluating and testing an AI system. Concretely, the key purpose at this stage is to ensure that the system meets the requirements set at the inception stage and performs as intended.[311] It is, in essence, built into the lifecycle as a risk mitigation tool, seeking to address challenges that may arise ex-ante.

Verification ascertains whether the design and development of an AI system or its component is in line with pre-determined requirements at earlier stages, and validation checks if the AI system fulfils its objectives within the context of its purpose.[312] An example of verification methods includes testing a chatbot's factual accuracy against the knowledge base it was trained on.[313] Validation can involve testing the prediction abilities of the AI system just before it is deployed, by inputting example prompts in a virtual environment.[314] Rigorous testing and evaluation can determine risk and failure points throughout the lifecycle, and help mitigate these to ensure not only compliance but also build confidence in the ability of the system to handle real-world complexities.

i. Identified Risks

The risks previously identified in prior stages continue to exist, but they may present themselves differently. This is because risks associated with data collection, such as poisoned data, privacy leaks, bias in outputs, etc., must continue to be addressed at the V&V stage. Other specific challenges and risks unique to the nature of V&V are rooted in the technical operationalising of testing methods, especially when concerned with the novel features of AI systems.[315]

Lack of Specific Models and Criteria

A primary issue is the absence of clearly defined validation models and criteria, which hinders the design of test cases for AI functions. Scholars have identified attributes of AI systems that make it difficult to create clear models and criteria for V&V, such as the dependency of behaviour on training data and subsequent uncertain behaviour regarding untested data. They also discuss the oracle problem as a further V&V concern, as explained below, which makes it difficult to clearly define the accuracy criteria for the correct outputs for each individual input.[316]

Isolated Model Testing

Another concern is isolated model testing. V&V processes must focus on testing the AI systems within the complete socio-technical ecosystem, and not just individual models.[317] End-user and AI interactions determine real-world performance, and isolated model testing would fail to consider the overall impact of the system in the environment it is deployed into.[318] The full effect of an AI system can only be felt once it is released to the wider public, and can be influenced by individual attitudes and user decisions.[319] Such user behaviour can introduce variability, leading to emergent risks from entanglement with all components of the AI system.[320] This can be understood as a manifestation of the butterfly effect, where one component's interaction (here, the user behaviour) with all the other components of the AI system can lead to a compounded effect. For instance, real-world testing, where such user behaviour is incorporated, can present ethical risks and dilemmas on bias amplification from flawed data, and the overall system exhibits greater bias than a single component[321] Further, the opacity of an AI system, and the knowledge and communication gaps between experts (the designers, developers and deployers) and the end-users, is a hurdle when designing questions that can be used to test for outcomes that may be present in the real-world.[322] User decisions made based on outputs generated by an AI system have significant real-world impact. While the developers may be aware of the intended use of the AI system and design it accordingly, they may not give sufficient consideration to pre-existing biases that may be amplified when post-deployment user input is introduced to the system. Such knowledge and communication gaps can lead to instances where bias persists due to prediction errors. For example, predictive grades based on 'typical performance of students' may reinforce socio-economic inequalities, even though the algorithm was designed to avoid such inequalities in grading.[323]

The 'Oracle Problem'

The 'oracle problem' is another crucial risk for testing/validating AI systems.[324] If the AI system is expected to function autonomously for an extended duration, it is designed with the ability to adapt or change its behaviour and outputs according to its environment and input.[325] It is nearly impossible to certify what these circumstances can present as, and what the desired outcome to verify and validate must look like. A related risk is the impossibility of accurately verifying because of the sheer scale and diversity of the environments. For example, in the automotive industry, verifying and validating AI systems designed for autonomous vehicles requires testing the cars for the possibility of fatal accidents. According to researchers, it is infeasible given the breadth of testing required to conduct adequate testing that determines a safe AI application. This is because it would require driving 433 million kilometres and an 'impossible' amount of time to conduct complete testing.[326]

Additionally, there are very limited standards for V&V for different AI systems, including procedural guidance and metrics. Firstly, existing best practices designed for testing conventional function-based software are rooted in well-defined inputs and within specified behaviours. However, these have been stretched and adapted for AI systems that are much wider conceptually, based on machine learning models using data-driven training.[327] Secondly, the required tools and frameworks are rare, sector-specific or focused on niche domains, and where they are available, they are scattered and non-comprehensive.[328]

ii. Governance Measures

Notable governance and technical measures are relevant throughout the lifecycle, such as data provenance and adversarial training, which continue to apply and can be operationalised as key measures in addressing identified risks at the V&V stage as well. Interestingly, assessing the AI systems for potential harm can involve scientific and philosophical questioning, where AI is viewed as a method towards understanding its proximity to mimicking human intelligence.[329] Other testing and V&V looks at evaluating performance based on the AI system's success within real-world, practical applications.[330]

Governance measures at the verification and validation stage

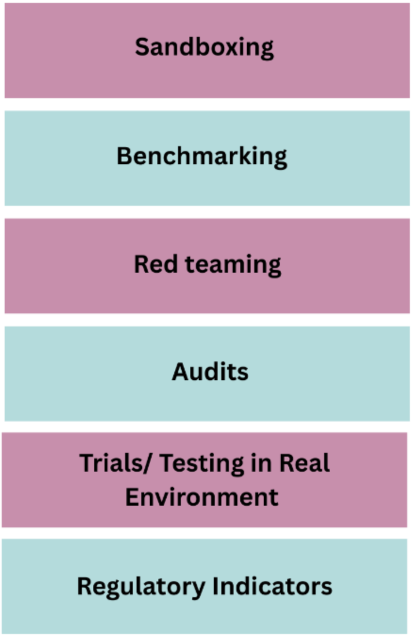


Figure 7: Verification and Validation Stage: Governance Measures

Sandboxing

AI sandboxes seek to foster innovation while safeguarding safety by testing within a controlled experimental environment in the pre-market stages.

Technical sandboxing is a form of contained testing, where the functions of an AI system can be executed under tightly controlled frameworks which can include runtime limits, restricted privileges such as limited access to the system's memory, etc.[331] This allows the developers to evaluate and test files or processes while mimicking real execution conditions, without exposing the system to compromise, such as malicious attempts like prompt injection.[332]

Regulatory sandboxing allows for this technical testing to take place in an environment with reduced regulatory constraints.[333] This creates a safe space for developers and legislators to work together, under regulatory supervision, with individual legal guidance.[334] As a governance mechanism, sandboxing can promote compliance with relevant regulatory obligations.[335] This is because conducting sandboxing testing during V&V encourages the improvement and implementation of legal certainty, best practices and evidence-based learning throughout the AI lifecycle.[336]

There are risks to regulatory sandboxing, and scholars argue that this may lead to developers evading responsibilities, lower safety standards and expose end-users to the very harms regulators seek to protect them from.[337] Careful and intentional operationalisation of sandboxing is necessary to ensure that the balance between innovation and regulation is maintained. To encourage this, the EU AI Act for example, calls for a sandbox plan - a document describing the objectives, timeline, methods and requirements for measures taken within the sandbox.[338]

Along similar lines of testing in a controlled environment, but distinct from sandboxing, are trials in a mock environment. Trials in a mock environment are a method of testing where the AI system is validated in an environment simulating an actual real-world environment. Such a trial can also be conducted in a direct or partial copy of the environment where the system will be deployed into.[339] This allows testers to look for malfunctions and correct them during pre-deployment. The potential damage is in a controlled environment and does not impact real-world performance negatively or cause harm to users.[340] Scholars present that trials can be cheaper in situations where the final environment is 'simple enough' to simulate.[341] For example, the trial of a music application was conducted by monitoring subjects' heartbeats while studying, thereby testing the ability of the system to recommend music that would improve efficiency. The system was used as intended, but the testing environment was 'mock' - in the way that the students were aware and studying in a replicated environment, and not when they would naturally be studying.[342] Given this simplified simulation of the real-world environment, there are limitations that follow. Scholars present that in a real-world environment, users' emotions and behaviour are influenced by various stimuli, and the whole breadth of these may not be represented in the mock environment.[343]

Benchmarking

Benchmarks are a particular combination of datasets that can include testing data, training data, and performance metrics.[344] Together, these represent specific tasks or abilities of the AI model and are selected as a shared framework to comparatively test the efficiency and safety of AI systems.[345] Conducting assessments using benchmarks operationalises AI safety efforts and increases standardisation due to the intentional selection of benchmarks and the decision-making process in developing benchmarking frameworks.[346] To further transparency and traceability, scholars opine that policymakers must ensure that applied and trusted benchmarks are well-documented, have clearly defined tasks and performance evaluation mechanisms.[347] Accordingly, the EU AI Act calls for the development of benchmarks and other measurement methods that can help assess accuracy and robustness levels of high-risk systems.[348]

Despite widespread reliance on benchmarks, researchers discuss concerns on the current use, such as ethical questions on what should be measured, according to which standards and what are the downstream effects.[349] As scholars have discussed, LLM benchmarks, for example, are hindered by limits of their creator's knowledge and may not be able to fully ascertain future and emerging AI capabilities, given they rely on the capacity of human understanding. As a result, these knowledge constraints of creators also impact how specialised and nuanced benchmarks can be, especially in more sensitive and contextual sectors like healthcare.[350] The performative and generative nature of benchmarks must also be considered, in the way that benchmarks not only describe and measure but also influence and actively shape the performance metrics that AI systems can be tested on.[351] Benchmarks are powerful and not neutral - they impact how AI systems are trained, tested, applied, and have economic, cultural and safety effects.[352] Large companies can shift their decision-making and business strategy, or raise massive capital based on the benchmark testing results.[353] Scholars also discuss how these large companies have a vested interest in the technology performing well, and can also exercise influence over the designing of the benchmarks. This can be a major conflict of interest in designing adequate benchmarks that can test for safe AI.[354] Specific concerns include ideas that mitigating AI safety risks that are continuously evolving and context-dependent are challenging for benchmarking as a V&V process.[355] Scholars recommend designing and applying benchmarks that are dynamic, continuously assessed for potential misuse, have rigorous evaluation protocols on validating and updating benchmark results, and can evaluate unintended consequences, alongside the performance of an AI system.[356]

Red teaming

Red teaming is a structured testing methodology that uses adversarial testing to assess the security and safety of an AI system.[357] The process involves simulated real-world attacks, misuse and abuse scenarios that target the weaknesses within a system.[358] These attacks can appear as prompt injection, data poisoning and model jailbreaks to test a system's resilience.[359] These 'threat models' are part of the interactive, iterative process and test the defences to gauge harmful behaviours such as violent content generation, and privacy issues like data leakage.[360] The verification processes can harness red teaming by engaging with external stakeholders like local civil society and advocacy groups, to incorporate risks of local malicious or authoritarian misuses that the AI system must be tested against.[361]

Audits

Audits as a governance mechanism are key in addressing risks in the development of AI systems and are typically concerned with investigating the systems and data, generating reports for both developers and users, and working towards transparency and explainability.[362] As part of V&V, internal audits allow for further accountability and traceability given the proximity to ongoing development procedures. Internal auditing can also address challenges that arise out of the 'blackbox' nature of algorithms, playing a key role in demystifying the opacity. By introducing structured oversight and verification methods, it promotes transparency through techniques like model documentation, where auditors require detailed logs of data inputs, processing logic, and output decisions.[363] This allows stakeholders to trace how algorithms arrive at conclusions, reducing reliance on unexplained predictions.[364] Adequate access to information during the V&V stage would allow for well-conducted internal audits.[365] Auditing helps accreditation with globally accepted standards, like the International Organisation for Standardisation.[366] There are also external audits, which are discussed later in the report as a governance mechanism for the Deployment and Post-Deployment stage.

Trials/ Testing in Real Environment

Real-world trials of AI systems are critical, since they are the sole non-hypothetical approach to testing whether an AI system is safe, trustworthy and effective under realistic conditions, beyond benchmarking and simulation-testing.[367] Real-world social contexts can pressurise AI systems, and analogous pressures are placed on the system in order to test it. Such trials can be conducted with increasing complexity, with small missions to the full scope of the AI system.[368] Rigorous trials can be laborious but they reveal possible issues in component collaboration, communication, sensors or usability of the system.[369]

The EU AI Act presents that the testing of high-risk systems must include real-world conditional testing and a comprehensive plan must be made, which is to be authorized by a market surveillance authority.[370] The real-world testing under V&V is required to last only as long as necessary, with informed consent, and suitable and qualified human oversight.[371]

Regulatory Indicators

While considerations around regulating AI can be traced in pre-existing and ongoing developments, industry practices and regulatory standards, there are limited obligations specific to V&V in the current regulatory climate. The EU AI Act indicates requirements where validation processes must be relevant, sufficiently representative, error-free and complete with regard to the intention of the testing mechanism.[372] Transparency of V&V methods and results is vital, as it serves as additional information for deployers, allowing them to interpret the AI system and use it appropriately.[373] The US NIST has also developed an AI Risk Management Framework.[374] NIST focuses on engagement with diverse internal teams, perspectives of stakeholders and external collaborators to improve the capacity for context understanding, assumptions of use, limitation grasp, etc. - which directly relate to ensuring robust testing mechanisms relevant to V&V processes are developed.[375] The framework emphasises a need for separation of duties, indicating that the developers and users of the AI system must be distinct from those conducting the V&V processes to ensure effective operationalisation of the risk mitigation efforts.[376]

Global South countries like Brazil have proposed new laws on governing artificial intelligence, which include guidance on developing sandboxes to foster innovation.[377] The law indicates requirements on validation for sandboxing and 'adoption of adequate parameters for the separation and organization of data for training, testing and validation of the results of the system.'[378] Further, the OECD AI Principles recommend testing and validation protocols, highlighting the iterative and not strictly sequential nature of V&V.[379] Continuous validation plays a key role in ensuring that risks associated with the oracle problem, for example, can be addressed in an ongoing manner, even post-deployment of AI systems.[380] It is only through continuous V&V that concerns around fault-tolerance, safety, or quality assurance can be resolved.

iii. Considerations for the Global South

As discussed, mechanisms under V&V critically depend on the quality of both the testing data and the team. Different people should bear the responsibility of training and testing; diversity should not be limited to the data, and must be present throughout the lifecycle. If the testing teams are not engaged locally, in regional contexts, V&V processes cannot adequately recognise risks specific to the local communities and the environment. AI models developed in the Global North are typically trained on data that underrepresents the diverse population, languages, culture and specific local context in the Global South. Testing of similar datasets as input directly without Global South context specific edits can lead to performance degradation and continuing bias when the system is deployed locally, because the system is designed and tested to perform at its highest ability in a Western Demographic and not the Global South.[381]

English-centric benchmarks are frequently poorly translated and are rife with errors.[382] They overlook local contexts like regional informal laws or traditions, and cannot capture the nuances required when using benchmarks to verify and validate an AI system.[383] Setting newer benchmarks that are Global South-sensitive with datasets on multiple categories ranging from literature to media, in both low and high-resource languages, require comprehensive efforts.

These benchmarks must capture both cultural breadth and depth to reflect local traditions and values.[384] One method to operationalise this is to include more substantive participatory approaches, and bringing in relevant stakeholders from local communities for consultations on inclusion, collaboration and ownership.[385] Participatory benchmarks enable performance measurement on broader dimensions, and can be designed and enabled to utilise human judgment by an individual with relevant knowledge and context.[386] For AI systems to be universally useful, they must meet the users where they are by respecting the regional contexts, and so must the verification and validation methodologies used to test them.

E Deployment & Post Deployment

The final stage of an AI system’s lifecycle can be further divided into specific stages: the initial deployment and post-deployment. Ongoing operation, continuous monitoring, revaluation and retirement are aspects of the post-deployment stage.[387]

Deployment is the stage at which the AI system is revealed to the target audience and can be put into use, provided it has been trained, tested, verified and validated. The risks at this stage are more pronounced than previously identified risks, since data that was not part of the training cycle, as well as unforeseeable inputs from users, and real-world impact of outputs, are no longer hypothetical.

i. Identified Risks

Users and impacted communities are at a risk from direct and indirect harms from AI systems which they are exposed to during real-world use, revealing vulnerabilities missed in prior risk mitigation and uncovering new threats. The following discussion focuses on the latter. Upon deployment, an AI system can present social harms, such as biased outputs that reinforce existing discrimination in policing or healthcare.[388] With newer inputs from end-users, privacy risks can be revealed.[389] Misuse of an AI system is a major risk post-deployment, where an AI system not intended for surveillance could be used to do so.[390] A further risk is the dehumanisation of personal healthcare decisions.[391] For example, the latter is part of a larger concern on the erasure of humanised healthcare systems, with increasing automated healthcare resulting in reduced doctorpatient relationships and individuals' medical autonomy.[392]

Data Drifting and Model Degradation

Post-deployment, AI systems bear the risk of losing accuracy due to data drifting. This phenomenon can occur in certain scenarios, where data collected and trained on begins to gradually differ from the data during the operation; it can in some cases have negative implications, leading to incorrect predictions or outcomes. When data drifts, it can lead to model degradation - where the AI system's performance declines with changes in the data or with changes in relationships between the variables on which it was trained and tested.[393]

Data drifting can be caused by the data sources exhibiting seasonal variations or changes in the user behaviour with evolving preferences, impacting input distribution.[394] A type of data drift is concept drifting, where the statistical relationship between input data and output/target variable changes with time. The risks associated with this are a direct challenge to the training of AI systems based on stationary data.[395] The extent of risk differs based on the application of the system. For example, AI systems used in diagnostic medicine have an impact on patient outcomes since the diagnoses depend on the reliability of disease prediction models; hence the continued/ long-term precision of the system post-deployment must be ensured.[396] Data drift in healthcare applications can occur due to differences between medical practices, training versus clinical use, changes in patient populations, disease patterns, etc.[397] For instance, in cases where data drifting leads to model degradation, real-world social harms can occur. When AI systems are deployed in predictive policing to identify recidivism, it can lead to an innocent person being misidentified as a possible repeat offender.[398] Automatic decision-making abilities of an AI system for sensitive topics such as crime control is a risky and unstable process, and requires interrogating the necessity of AI application in such fields.[399]

Model Inversion

Model inversion is a privacy risk where attackers seek to obtain sensitive information from AI systems, specifically machine learning models. Once an AI system has been deployed, a hostile user can reverse-engineer the learning and training procedures to reveal information that was part of the original training data.[400] Strategic querying exploits the tendency of an AI system to retain knowledge of training data, and attackers analyse outputs to deduce or reconstruct personally identifiable information that could include biometric information, medical records or financial details.[401]

Additional Risks

Previously discussed risks like data poisoning embedded into training data that lead to malicious backdoors, which may have been missed during the initial testing, can impact the accuracy and user experience once an AI system has been deployed.[402] Malicious backdoors, in particular, can weaken the system and reduce its trustworthiness, and make it vulnerable to manipulation once novel data is fed into the system as user inputs.

There are on-ground and practical concerns with AI system governance that persist throughout the lifecycle, such as infrastructure instability and low digital literacy among local deployers, oversight personnel and end-users. There are also concerns with a lack of information provided by AI developers to deployers and users, including a lack of proper documentation on the purpose, possible use cases, training data, V&V undertaken, human oversight requirements, and incident reporting mechanisms. Defining clear and traceable selection processes for responsible and expert personnel are essential to mitigate concerns like oversight gaps and accountability failures. Existing risks include the exacerbation of inequalities and vulnerability of users due to weaker oversight. Notably, there are also safety vs functionality trade-offs due to a rapidly deployed AI system given the innovation mindset.[403] When faster deployment is prioritised over sufficient risk and harm assessments and oversight mechanisms, it can expose the deployers' organisations to fines and operational errors.[404] All these are specific concerns that continuous monitoring must account for prior to asserting the accuracy and quality of an AI system.[405]

iii. Governance Measures

The governance and technical measures for the risks that present at this stage are similar to those discussed previously, and have a continuous nature to them. Risk mitigation and governance measures during and after deployment should account for abuse and accidental misuse of an AI system, social harms, inadequate human monitoring, and reporting on the purpose and limitations of the AI system for users, etc.

Deployers and providers of high-risk AI systems applied in sensitive environments also necessitate broad mechanisms such as sharing instructions on use for end-users, conducting fundamental rights impact assessment and conformity assessments, logging and sharing of technical information with the relevant stakeholders including accuracy metrics and record keeping.[406] The specifications come from the EU AI Act, but are indicative of governance measures that are omnipresent, some of which overlap with mitigation techniques discussed below.

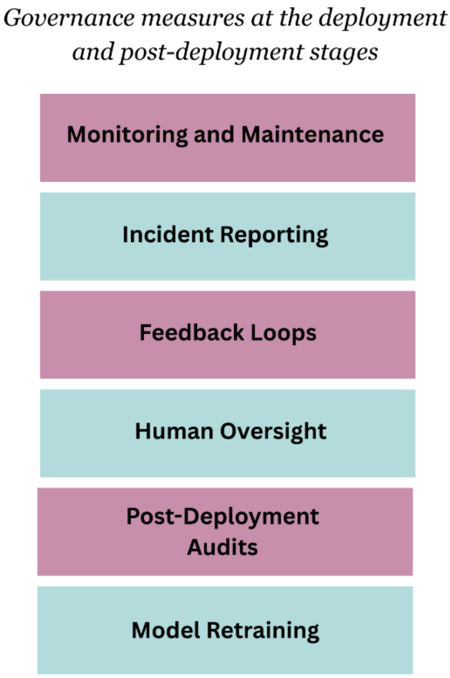

Governance measures at the deployment and post-deployment stages
Monitoring and Maintenance
Incident Reporting
Feedback Loops
Human Oversight
Post-Deployment Audits
Model Retraining

Figure 8: Deployment and Post Deployment Stage of an AI Model: Governance Measures

Monitoring and Maintenance

Monitoring and maintenance are necessary to ensure the AI system's robustness, ethical compliance, stakeholder trust, and safety of users and impacted communities. Specifically, to address data and concept drifting, drift detection frameworks are required.[407] Proactive approaches to drift detection require regular monitoring of the model performance based on pre-determined metrics, ongoing learning and collecting data. Tracking performance across different user groups are some ways to study the root cause.[408]

Behavioural pattern and anomaly detection is an element of ongoing monitoring which can help address model inversion risks.[409] By tracking and analysing repetitive, near identical prompts, possible model inversion can be detected early. For example, a single user submitting over a certain number of semantically similar queries can be flagged, like guardrails in a chatbot application that are triggered if a user input violates the safety policy of the deployed system.[410] Output screening and content filtering are important steps to be taken during the pre-deployment phase that can impact post-deployment risks, especially model inversion and malicious use.[411] Scrutinising what outputs the AI system creates can help govern the leakage of personally identifiable information during malicious attacks in a proactive manner.

Post-market monitoring is a requirement under the EU AI Act for high-risk AI systems, where systematic collection, documentation and analysis of relevant data allow the system providers to enable continuous evaluation.[412] The EU AI Act also indicates serious incident reporting requirements.[413] Similarly, the NIST AI RMF also recommends continuous vigilance, monitoring and human oversight of AI-systems.[414]

Logging (including automatic logs) and record keeping of the information collected as part of the monitoring is necessary to ensure traceability and foster accountability, and is also a requirement under the EU AI Act for high-risk systems.[415]

Incident Reporting

A necessary governance mechanism is the availability and encouragement of AI incident reporting. The OECD defines an 'AI incident' as an event where an AI system results in individual, environmental or societal harm due to malfunction, misuse of bias.[416] The availability to report an incident fosters trust amongst stakeholders, and creates space to have a risk or impact-based concern addressed.[417] Per the EU AI Act, for high-risk AI systems, incident reporting is a vital mechanism, enabling awareness and communication amongst deployers and end-users. The EU AI Act requires deployers to inform the providers of an AI system, distributors and relevant market surveillance authorities once a serious incident has been identified.[418] It is important that the process is straightforward, evidence is collected and the responsible individuals within the AI lifecycle are identified in order to investigate, address and adapt the system as required. Incident reporting mechanisms also act as a compliance measurement tool, enabling authorities to evaluate the shifting risks and associated compliance requirements, as the AI system continues to evolve once it has been deployed.[419]

Incident reporting can also be employed by the deployers themselves, where categories of internally identified incidents depending on the risk-level must be reported to regional authorities and other stakeholders. These can range from voluntary to mandatory reporting, based on the consequences of said incident, ensuring accountability.[420] The gravity of the incident determines whether it is mandatory to report or not. As an example, the new Brazilian artificial intelligence law indicates requirements for developers and deployers to report serious incidents to competent authorities.[421]

Per the OECD, complaint addressal forums and incident reporting are the first steps in creating a feedback loop, allowing for the communication and recording of any incident where an AI system may have resulted in individual, environmental or societal harm.[422] Such reporting can also help stakeholders such as policymakers assess the harms in light of building governance frameworks. The Ministry of Electronics and Information Technology, Government of India issued the India AI Governance Guidelines, where the creation of a national database for incident reporting has been suggested. This database is intended to act as a source of information for policymakers on real-world risks and harms, and also inform the development of risk frameworks. The recommendations encourage voluntary incident reporting by developers, and creates space for private organisations, sector-specific regulators and individuals to participate.[423]

Feedback Loops

Creating and implementing a feedback loop is key. A feedback loop allows the deployers to collect, analyse and learn from direct user data to operationalise a cycle of continuous improvement. Feedback can also be collected as consumer interactions and reviews, email surveys, etc.[424] Deployers can then engage with the incident reporting knowledge and feedback to maintain and improve the AI system.[425] In the India AI Governance Guidelines, the Ministry of Electronics and Information Technology, Government of India discusses the development of a structured feedback loop through reporting, which can guide policymakers on emerging risks, patterns of harm and their impact.[426]

Human Oversight

The 'human in the loop' mechanism, discussed in the model design and training stage, is also a key governance mechanism to prevent over-reliance on automated systems in the deployment stage. This is particularly significant in critical deployment sectors such as hiring practices, medical diagnostics, or health insurance.[427] Ongoing monitoring and control of an AI system requires human involvement and informed personnel capable of addressing issues that may arise during development and post- deployment of the system.[428] Human decision-making can be pre-defined, with designated tasks such as explicit approval before an AI system takes a certain step, or requiring approvals adhoc, such as intervention during irregular inputs leading to erroneous outputs .[429] The EU AI Act emphasises safeguards for individual rights, with transparency at its core. The EU AI Act mandates human oversight in high-risk AI decision-making, like healthcare, and requires that the personnel are competent, trained and authorised.[430] Human oversight is also required for operationalisation of other principles for safe AI, such as explainability, where the ability to understand and interpret AI systems underlines ethical deployment and post-deployment processes.[431] Techniques such as reinforcement learning from human feedback, are also part of the human oversight mechanism, and are employed to mitigate harmful outputs that may present themselves once an AI system has been deployed.[432]

Post-Deployment Audits

Conducting regular independent third-party security assessments and audits of the AI systems is necessary to determine vulnerabilities. This includes bias and fairness audits to ensure the overall safety of end-users. Auditability refers to the levels of access to information, quality of procedural documentation, and the ability to be systematically examined, analysed and understood.[433] Thoroughly conducted audits can indicate whether the principles of AI safety such as transparency, explainability and accuracy have been fulfilled. Third party audits should not just be permitted, but encouraged, including by civil society organisations, researchers and AI ethicists. The results and feedback from these post-deployment audits work alongside mechanisms such as maintenance and also work towards model retraining, as discussed next.

Model Retraining

Model retraining is an important governance measure - it indicates the willingness of developers and deployers to ensure continuous improvement of their AI system in order to maintain its accuracy and usefulness based on the initial purpose. Adaptive learning algorithms must be incorporated into the AI systems, along with the possibilities of human intervention and updating of data to retrain the model where it is unable to adapt and maintain accuracy. A regular retraining schedule depending on the environment and industry the AI system is deployed into, combined with a 'rolling window' of training - where the most recent data is regularly incorporated to maintain relevance can mitigate risks of the AI system's degradation.[434] Incorporating historical and new data requires a delicate balance between newer but less static trends and long-term patterns that have been previously recognised and verified in order to train the AI system.[435] Such retraining is an operationalised mechanism of a mandatory requirement under the EU AI Act, where providers of high-risk AI systems are required to take corrective actions if they believe the system no longer conforms with its requirements.[436]

iii. Considerations for the Global South

Various elements of heightened risks in the Global South are amplified post-deployment. Previously discussed considerations, such as low infrastructure availability, developing regional legal accountability mechanisms, inadequate reporting tools, etc. continue to present challenges.[437] Imbalanced development and staggered iterations of scientific advancements are unfortunate realities when deploying AI systems in the Global South, and must be approached carefully and intentionally in order to avoid exacerbating social harms.[438]

Historically disproportionate power dynamics continue to manifest even in technological deployment, and require differential application of AI systems, especially in sectors where racial and gendered information can impact the decision-making abilities of an AI system.[439] The sector-specific risks are necessary to highlight, for example, in hiring, where the AI systems risk reproducing systemic racism by relying on historically biased data and opaque algorithmic processes.[440] AI application for these purposes is a sensitive and risky field of application, especially with the multitude of human variables involved.[441] Predictive algorithms that are not adequately sensitised and contextually trained can continue to perpetuate discriminatory tones in studying linguistic patterns.[442] For example, hate speech detection algorithms identifying Black vernacular as 'toxic'.[443] With hate speech detection, there are further challenges in advancing research on South Asian languages, including the limited availability of data, data that is code-mixed, i.e. a mix of regional languages written in roman script and emojis.[444]

Consider the model inversion risks discussed earlier that can lead to biometric data leakage with targeted prompt injections. Such concerns around privacy are further exacerbated due to lower digital literacy and lack of awareness around sharing personally identifiable information online.[445] Users with limited understanding of digital privacy concerns are less likely to have foresight on potential harms they may face.[446] With drift detection, localised data may be of poor quality, non-standardised or scarce; and continuous vigilance as to the quality is complicated when seeking to prevent model degradation. This challenge arises because real-world data from diverse regions often includes variations like regional dialects, inconsistent collection methods, or limited samples that diverge from original training sets, requiring constant adaptation to avoid performance drops.

Models conceptualised in the Global North and embedded into AI systems are typically developed and trained on data from the Global North.[447] Their accuracy, once deployed in the Global South, can be impaired. With limited resources spent on post-deployment monitoring, lack of transparency, limited regional oversight and relaxed compliance and regulatory requirements, errors that may pose significant harms may not be immediately detected, let alone rectified.[448] Post deployment monitoring can be improved by documenting instances of negative impact, with examples on 'toxicity scoring' acting as reverse pedagogy - where impacted end-users can expose an AI system's pitfalls and limitations, eventually allowing for improvement in subsequent updated versions of the technology.[449] The flow of information must not be limited downstream, so to speak. Culturally rich and diverse digital ethics can help mitigate, to a certain extent, issues around lack of awareness amongst both deployers and end-users.[450]

The robustness and institutional resilience of an AI system is vital for continuous performance. Targeted localised bias auditing is necessary to ensure that an AI system is operationally robust based on the market it is deployed into, especially in the Global South. These audits and other monitoring systems must look at local categories like caste, socio-economic class and regional dialects in languages - categories that may not be extensively studied in the Global North. The monitoring can take place through impact assessments and audits, before and after deployment, and involve local communities and civil society organisations. In Brazil, the proposed Artificial Intelligence law also introduces requirements for deployer-led impact assessments for high-risk AI systems such as biometric identification.[451] Scholars have recommended a ‘Decoloniality Impact Assessment’, as an impact assessment methodology that is context-sensitive and evaluates AI systems in relation to the ‘inherent colonial legacies, global power asymmetries and epistemic injustices.’[452] Such assessments focus on questioning how the AI lifecycle and generic risk mitigation measures are not only insufficient in the Global South contexts, but in fact can reinforce structural inequalities, marginalise local knowledge pathways and continue to benefit from pre-existing exploitative systems.[453]

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