International Academic Institute for Science and Technology

International Academic Journal of Social Sciences
Vol. 13, No. 3, 2026, pp. 15-29.

ISSN 2454-3918

International Academic Journal of Social Sciences

www.iaiest.com

Ethical Artificial Intelligence Adoption and its Societal Implications in Emerging Economies

Budi Santoso [a*], Siti Rahmawati [b]

[a*] *Indonesian Institute for Digital Development Research, Bandung, Indonesia.*
[b] *Indonesian Institute for Digital Development Research, Bandung, Indonesia.*

Abstract

The adoption of artificial intelligence is increasing in emerging economies, but the regulatory environment for governing this technological adoption is developing more slowly than the technology itself. In this paper, the ethical implications of AI adoption in emerging economies and the resulting societal implications due to lagging governance will be investigated. Based on a systematic literature review, policy analysis and cross-country comparison of AI principles, the paper will establish an interdisciplinary analytical framework comprising four interrelated dimensions: infrastructural and data sovereignty constraints, labor market and distributional implications, governance and regulatory capacities and social trust and legitimacy. Specifically, the paper argues that ethical risk in emerging economies is structurally different from ethical risk in mature economies, where there are concerns about algorithmic accountability in relatively well-equipped regulatory environments. The emerging economies, on the other hand, have a different and more complicated situation, where infrastructural constraints, skills gaps, difficult policy environment, uneven quality of education and lack of data protection regulations intersect with market power externally. The framework will be combined with an interdisciplinary research methodology involving comparative policy analysis, survey and interviews with firms and stakeholders' deliberation. This paper presents an AI ethics framework that is context-based and one that views representation, data sovereignty, and distributive justice as primary design and governance issues rather than secondary compliance matters.

Keywords: Ethical Artificial Intelligence, Emerging Economies, AI Governance, Digital Divide, Data Sovereignty, Algorithmic Accountability, Distributive Justice, Regulatory Capacity.

DOI: 10.71086/IAJSS/V13I3/IAJSS1319
Received: 17 June 2026/Revised: 03 July 2026/Accepted: 25 August 2026/Published: 30 September 2026

Introduction

The development of AI has turned into a main tool for economic modernization in emerging economies, and the speed of adoption is increasing. In the developing world, adoption of AI and digital technologies is growing and there will be a need to develop the required legal frameworks to facilitate the proper use of AI and digital technologies (Raihan et al., 2024). There is the gap between the availability of AI and its governance which is the main issue in this paper. AI has the potential to transform the situation in these regions, but it is restricted because of the lack of infrastructure, skills, and complicated policies with ethical and digital divide being the main gaps in existing literature. The outcome of such a situation is the governance gap that is not simply a gap to be filled in time, but it has its own dynamics (Roche et al., 2022).

The scale of such a structural condition is reflected in the policy literature. Initiatives such as the proposed Artificial Intelligence Act and General Data Protection Regulation of the European Union in 2018 are geared towards combating any misuse of data and AI in the Western world, which implies that the regulatory measures that define global ethics of artificial intelligence have been crafted and tested in the context of high income countries (Aderibigbe et al., 2023). The imposition of a framework devised in one institutional setting in another is far from being a neutral process. An AI solution that can be created in the Global North could be incompatible with the ethical standards in the Global South, and therefore be inappropriate for such settings, and an AI solution that originates in the Global North may not live up to the potential of many AI for good missions (de-Lima-Santos et al., 2024).

Economic and political aspects are connected with the distributional impact. The AI life cycle excludes developing countries since a large number of international private companies and developed countries have played a significant role in designing, implementing, deploying, and applying AI technologies. There are some consequences of the exclusion. Well-established companies can make large investments for adopting AI technologies while small organizations cannot; in addition, data protection and governance become complicated in the Global South because many non-Western, Educated, Industrialized, Rich, and Democratic (WEIRD) countries do not have proper regulation and infrastructure for controlling data collection, storage, and utilization and thus the populations of such countries become victims of exploitation by multinational companies and countries . Moreover, further analysis of AI decision-making in finance shows that automated decision-making algorithms demonstrate bias and lack ethical governance and transparency of decision-making that leads to unjust results and unequal access to finance, poverty reduction, and sustainable development goals are endangered because of exploitation of developing countries through AI technology for collecting data and making profit (Sarma et al., 2023).

Two additional factors that influence the problem include the material factor and the human capital factor. First, infrastructure is a key driver in the implementation of AI. Although western countries have put in significant efforts in creating advanced infrastructures, developing countries in the Global South find it difficult to create digital infrastructures and therefore access reliable internet services needed to access the innovations and solutions provided by AI. The other factor that influences the problem is human capital. In this case, the capacity to educate people and develop skills for innovation in AI is a critical issue in the Global South, considering that lack of equal access to education and training, particularly in Science, Technology, Engineering, and Mathematics (STEM), increases the gap between people in developing countries and those in the developed world (Bulathwela et al., 2024).

Empirical literature has started working on these conditions, but no effort has been made to combine them. Empirical review studies have covered the adoption of artificial intelligence in healthcare, education, agriculture, manufacturing, services and media in the Global South along with the policy suggestions for policymakers, academia, entrepreneurs, and NGOs. The research on ethical perspective of AI confirms the fact that ethical practice of AI avoids any kind of misuse of technology, and this will help in having good AI for developing countries because, by avoiding biases and protecting privacy and security, stakeholders will be contributing towards the construction of AI systems according to the ethical standards. Policy literature has introduced one more condition that AI governance should require an additionality towards Sustainable Development Goals, and it should be verified through algorithm auditing, and pre-emptive regulatory mechanisms should be introduced to avoid the situations where AI hinders these SDGs (Truby, 2020). Constructive proposals for inclusion are also available, in which the starting point is a four-tiered framework for public policy practitioners and governments which starts with the recognition that AI systems are global by nature – developed in one part of the world and implemented elsewhere – thus requiring a global alliance for AI standardisation and rating.

What is still missing is the perspective which views all of these perspectives as one whole. The research into infrastructure, labour markets, regulations and trust has been separate, therefore the relationships and interactions that are shaping the outcomes in developing economies are under-theorised (Borines et al., 2024). One more obstacle is

that of representation – even though international organizations have strived to create and support global AI networks as well as represent the interests of developing countries and marginalised populations in them, the underrepresentation persists since these networks encourage interaction and cooperation between different stakeholders like experts, industries, and regulators mainly in the developed countries – Global Partnership on AI, established in 2020 after discussion in G7, encourages international cooperation in trustworthy and responsible AI, however, the experts involved in its working groups still mainly come from the developed countries .

In response, this paper provides an analytical framework for ethical AI adoption in emerging economies across four dimensions: infrastructural and data sovereignty context, labor market impacts, governance and regulatory capabilities, and social trust and legitimacy (Dwivedi et al., 2019). The paper makes its contribution by specifying how these dimensions interrelate, by claiming that ethical risks in emerging economies are structurally different from ethical risks in developed countries, not just more acute, and by proposing a validation design. Specifically, the analysis relies on the recent literature and policies rather than on single-country examples, such that the framework can be applied to the diverse range of emerging economies while taking into account the specificity of each country's situation. AI inclusive for social good is needed to have a participative policy approach that fosters fairness and access as well as societal benefits (Moon, 2023).

The paper is structured as follows. Section 2 provides the literature review of AI adoption in emerging economies, its ethical implications and governance reactions. Section 3 describes the research gap and contributions. Section 4 offers the analytical framework. Section 5 gives the methodology and research agenda. Section 6 outlines the policy implications, before Section 7 concludes.

Literature Review

Adoption Patterns and Infrastructural Preconditions

Research regarding AI adoption in the Global South has progressed enough for sectoral trends to be observed, though unevenly. A systematic review of 100 scholarly papers explored AI adoption in the spheres of healthcare, education, agriculture, manufacturing, service industry, and media, pointing out crucial research gaps and challenges faced by different regions, including ethical challenges and the problem of the digital divide. What the review concludes about is the fact that while AI has great potential, it remains inaccessible to these regions due to their infrastructural shortcomings, lack of skills, and complicated political frameworks, and that specific recommendations need to be developed for governments, academics, entrepreneurs, and NGOs in order to customize the use of AI and overcome these barriers in the pursuit of economic and social equity.

The infrastructural precondition is elaborated upon elsewhere. Infrastructure building has been an important factor in the introduction of AI technologies; Western countries have poured substantial effort into building strong infrastructures, while many developing countries continue to find it difficult to provide internet connectivity to their residents, and this difference impacts both the availability of AI applications and the ability to participate in the digital economy of the global world. The extent of the underlying divide is well documented: more than half of the world's population is without internet access, and there are entire communities which do not even have any data to feed any AI system. The latter point is analytically relevant but often overlooked. Lack of data on a particular community is not just a challenge for the use of AI created elsewhere; it is a challenge to create any AI for them at all. Without data, no AI system can be expected to be useful for this community, and this fact is reflected in the overall numbers.

The second pre-condition revolves around human capital. Education and the development of skills required for AI innovation and implementation continue to be significant hurdles in the Global South, where the problem of unequal access to education exacerbates the problem of the digital divide, and inadequate education and obsolete curriculum hamper the development of skills related to AI among youth. The above problem has an important implication with regards to governance. Auditing, contesting, and regulation of algorithmic technologies necessitate technical skills, and in cases where technical expertise is limited, there is a lack of sufficient personnel to run such accountability mechanisms.

The implementation of artificial intelligence in emerging markets needs to be viewed in the context of technological opportunities, institutional capabilities, and the socioeconomic characteristics of people who would utilize those systems. While artificial intelligence technologies are gradually becoming used in healthcare, education, agriculture, manufacturing, finance, and public administration sectors, the capacity to employ them varies widely depending on location and community. The availability of digital platforms is not synonymous with creating all the conditions necessary for successful AI implementation. Connectivity, cost-effective computing, digital services, and relevant data sets are also critical factors in ensuring the applicability of AI applications to community needs. In most

developing regions, such shortcomings prevent the emergence of locally tailored solutions and promote the reliance on the products that are developed in completely different socioeconomic contexts. Hence, the adoption of AI technologies needs to be studied not only in terms of the number of organizations that use AI but also in light of the infrastructure and other resources available for sustainable AI implementation.

Infrastuctural readiness is related to the capacity of local organizations to engage in the creation and management of artificial intelligence. The lack of connectivity and enough locally produced data might force communities to rely on external platforms and data sets which might not reflect their specific socioeconomic and cultural features. This aspect can affect the quality of recommendations and cause challenges with detecting errors and discriminations. Besides, insufficient technical education might result in the shortage of experts able to create, support, and check AI tools. For this reason, the development of infrastructure and the creation of human capital can be viewed as linked prerequisites. Digital connectivity, availability of relevant data, and technical skills can help to build a stronger base for AI use. Such conditions become especially important for the participation of emerging economies in all stages of AI development.

Distributive and Labour Market Effects

AI adoption's distributive effects in developing economies arise from three mechanisms: the capabilities of firms to adopt AI, the concentration of markets, and the conditions of access to technology outside of the firm. The first mechanism arises from the fact that the adoption of AI technologies is costly and thus larger firms, in contrast to smaller firms, can afford to make these investments. The implication of this distributive effect for development strategy is straightforward: if the adoption of AI technologies is costly for small firms, the diffusion of AI could result in a skewed distribution of productive capacity.

Regarding the second channel, the way of how particular sectors adopt AI is a good illustration. In the news business sector, big media companies are adopting and applying AI technologies and solutions in their practice, whereas small media companies rely on platform funding to try out particular AI technologies and solutions. Such a dependence on platform funding means involving another party in the process of both editorial and technological decisions, which has consequences for pluralism that do not fit the concept of traditional competition. Regarding the third channel, the conditions of access determine the distribution of the value between parties. The threat of exploiting developing nations via harvesting of data and profit from AI technologies poses a threat to the goal of fighting financial crimes and corruption; people from non-WEIRD countries lacking the legislation and resources to regulate the processes of collecting, storing, and utilizing of data become easy targets for exploitation by multinational corporations and foreign states.

Financial services offer perhaps the clearest illustration of the result of uncontrolled algorithmic decision making. The objective of financial inclusion is compromised by an incomplete and uncontrolled approach to the design and deployment of decision-making algorithms that make financial decisions impacting customers, whereby automated decision-making algorithms have shown a tendency to be biased, have lacked ethical governance, and have limited transparency in the rationale behind their decision-making, thus producing discriminatory effects and increasing inequality in access to financial services. Three characteristics are worth highlighting here. Bias refers to the distribution of the outcomes. Lack of ethical governance refers to the lack of an internal control mechanism. Limited transparency refers to the inability of the persons affected to understand and challenge the decision.

Another aspect of the economic impact of the application of AI is the issue of distributional implications with respect to technological investments, work opportunities, and productivity of organizations. Large organizations might be able to afford to invest in more technologically advanced uses of AI, while small businesses might find themselves at odds with regard to the implementation of advanced AI technologies owing to the investment costs, technical difficulties, and dependence on external platforms. This might affect the competitive advantage of firms and lead to inequality in productivity gains for businesses across sectors. Once larger companies get access to advanced analytical systems, automation, and digital infrastructures, they will become more powerful compared to smaller organizations. All this will exert even more pressure on small organizations working with insufficient resources.

Further proof of the uneven distribution of benefits and costs associated with AI adoption comes from its impacts on the labour market. The automation of tasks with intelligent systems can save time spent on their performance and assist in creating new functions for occupation, yet the change may cause problems to those workers who have skills that do not correspond to the new technological requirements. Those workers that have access to education, training in digital technologies, and professional development will be able to benefit from new employment opportunities, while others with no means to gain these resources will face more troubles. This becomes especially relevant in countries with inequality in access to quality education and professional training. In order to introduce AI responsibly,

there should be a connection between it and workforce development and training, and thus assistance to affected workers.

Governance Capacity and Regulatory Frameworks

As per the literature in the field of governance, there exists a structural asymmetry. The Artificial Intelligence Act and the General Data Protection Regulation of 2018 are seen as an effort to counteract the unethical use of data and artificial intelligence technology in the western world. However, in the southern world where the adoption of AI and other digital technology is growing, these economies will have to formulate their respective legislative framework in order to encourage the ethical use of AI and digital technology. The language used above is important in that the need is for developing legislative frameworks and not importing them. Since it is the need of these economies to formulate their respective legislative frameworks, this analysis will focus on regulatory frameworks to ensure the ethical use of AI in the southern world.

In those places where governance frameworks do exist around the world, there is a level of convergence in the content, but there is no convergence in its application. This research analyzed a dataset of 463 AI documents from the Council of Europe tracker on references to 11 key anchor terms and more than 60 codes related to the Global South and other underrepresented groups. This research came up with a representation deficit with serious repercussions – AI policies and principles should reflect the diversity of the global community that is implementing AI and underrepresentation can actually exacerbate any potential blind spots. There are very difficult underlying conditions against which the problem of representation deficit stands. More than 700 million people, or 10% of the global population, live in absolute poverty. Moreover, inequality on a variety of enhanced capabilities, including advanced technologies, is growing, the difference between high and low human development countries is growing regarding access to digital technologies such as mobile phones and broadband internet connection. In cases where there are international forums that seek to coordinate the development of responsible AI, the imbalance continues: The Global Partnership on AI, established in 2020 after discussions in the G7 forum, seeks to foster international cooperation toward trustworthy and responsible AI; however, experts in the group's working bodies are mostly from developed nations.

There are additional institutional implications to the governance gap that go beyond rules creation. The gap between the possible contribution of AI and AI actions to social welfare has not only failed to shrink, but has even increased with the rate of technological development, and the international community has been poorly prepared to meet different challenges and address potential threats to humanity, biases toward the less fortunate, and uneven distribution of benefits by country and by individual social standing – which has hindered the attempt at inclusivity in AI. In addition to this, several biggest technology corporations employ a business model, which allows deploying an experimental version of AI with relatively little restriction from outside, and since this unregulated deployment creates risks for the achievement of Sustainable Development Goals, especially in respect to the developing nations, the logic goes that those companies should not be allowed to act outside of the scope of regulations. The solution is both processual and substantial: a set of regulatory requirements to be placed on AI developers and coders, with compliance ensured by algorithmic auditing, and the necessity to provide Sustainable Development Goal value from AI governance frameworks.

Constructive solutions on how to overcome the participation gap can be found at the policy level as well. Due to the fact that AI technologies have a global reach in terms of development in one corner of the world and deployment in another, it is important to form a global coalition for AI standardization and rating, and this initiative is presented as the first among four pillars of the policy strategy. This approach recognizes that unilateral regulation of these systems on the national level cannot apply due to the nature of AI systems, and that standards should be enforceable on the territories of their application.

When it comes to developing the regulatory capacities of emerging economies, it is necessary to take into account the ability of the institution to convert legislative provisions into real actions of governance. The presence of legislation or policy guidelines on data protection and artificial intelligence does not necessarily mean that an organization will adopt responsible behavior or that those who are affected by automated decisions can oppose them. There should be trained staff, appropriate technical resources, access to independent expertise, and mechanisms for reviewing the work of AI developers and providers. Otherwise, the legislative framework can be reduced to simple policy statements but fail to bring changes in the design and operation of AI systems. It is especially true for developing economies that have to manage the rapid development of digital technologies at the same time as having limited resources for doing so.

The second issue pertains to the involvement of emerging economies in international dialogue on AI standards and ethical guidelines. As AI technologies are typically developed in one state and then used in many other countries, their

governance requires collaboration beyond national and organizational borders. Yet international policy dialogue may not necessarily reflect the experience of those communities facing diverse technological and social issues. Poor representation can mean that the standards developed will take into account the needs of advanced economies without considering the obstacles experienced by developing economies. Increased involvement in international governance networks can help incorporate these factors into the policy dialogue and thus enhance the appropriateness of global AI standards. It is important that the participation includes representatives of policymakers, researchers, civil society, technical specialists, and communities from emerging economies. This can help ensure a balanced environment for governance where international collaboration is complemented by local regulation.

Trust, Equity, and the Limits of Technological Remedy

The fourth aspect of the analysis comes from the literature on adoption and trust. The implementation of ethical AI ensures safety from any form of misapplication of AI technology and contributes to the responsible and positive application of AI technology in developing nations, which is important for gaining trust and responsible use; through bias prevention, promotion of fairness, and ensuring privacy and security, one can contribute to the creation of ethical AI. Trust in this regard is not just a communications objective, but the result of ethical performance.

This is supported by research into the area of education, which warns of the dangers of considering technology as a self-contained solution. If the trend continues in its current form, then AI in education could widen rather than reduce educational inequality, due to the techno-solutionist approach that considers technology to be the easy, perfect solution to difficult problems in the real world. This principle holds true as much for financial inclusion, agriculture, and public services delivery, where the problem lies with institutions rather than technology.

Ultimately, the digital equity literature outlines what a root cause approach entails. It calls for context-specific actions to better understand the root causes of the digital divide, not necessarily the symptoms thereof, through collaboration with government, civil society, NGO, and community stakeholders. The persistent structural inequalities in connection, cost, and literacy are causing marginalized people to be locked out of education, healthcare, economic opportunity, and civic engagement. In the case of AI specifically, this means that measuring adoption rates is not enough; benefit and harm distributions should be assessed among differentiated groups, and the solution should involve those stakeholders, not simply be done to them.

The concept of trust in artificial intelligence needs to be perceived not as the result of responsible functioning but rather as the result of responsible functioning and institutional accountability. People would be willing to use AI-powered services if they feel that they can understand the process of making decisions, comprehend the reason why their data is being used, and receive adequate explanations if there is some effect on them. On the other hand, automation that brings about unjustified disadvantages or discriminative decisions may undermine the trust of people, especially if there is no mechanism for them to oppose such decisions. The problem is especially urgent in finance, education, healthcare, and public sector because in these spheres AI might affect the availability of certain opportunities and resources. Thus, building trust is not only about developing sophisticated digital services; it also implies transparent, private, fair, and accountable practices.

The limits of technology-based approaches are another indication that AI by itself cannot solve structural issues emerging from institutional deficiencies and socioeconomic disparities. For instance, the introduction of AI-enhanced educational platforms will hardly lead to better educational results in case students do not have an internet connection or devices, or teachers are not properly qualified, or the learning environment is unsuitable. In turn, automated financial services cannot yield any real inclusiveness in case people do not have accessible access to financial infrastructure or the decision-making algorithms work without sufficient measures. Thus, one should evaluate all the technological solutions in the light of the broader system in which they are introduced. Any intervention should be aimed at resolving the very issues preventing communities from benefiting from technologies. The cooperation of government agencies, civil society, NGOs, private companies, and communities can be instrumental in this regard. In this sense, trust and equity are the markers of whether the adoption of AI yields positive social effects.

Research Gap and Contributions

Three gaps arise from this review.

Firstly, there is the Gap of Context Transposition. The prevailing ethical approaches to the management of AI have been created in and for high-income regions, and developing countries are encouraged to craft their legislation for AI separately from what exists elsewhere. From a comparative perspective, there is confirmation of the core issue: solutions to AI problems devised within the Global North may not fit the ethical system of the Global South and

therefore not be applicable. But what is lacking here is a theoretical understanding of how certain aspects of the ethical risk can vary depending on context.

Secondly, there is an Integration Gap. The simultaneous presence of infrastructure challenges, shortage of skills, and complex policy environment is well known, as is the vulnerability of populations due to the lack of a legal framework and market power. This combination is observed but almost never analyzed as an interaction effect. It is essential since precisely through this interaction the harm occurs: a population whose data are not regulated and whose regulators do not have sufficient knowledge is vulnerable not to two distinct threats but to one compounded one.

Thirdly, a Representation and Measurement Problem. An analysis of 463 policy documents analyzed through 11 anchor concepts and more than 60 associated codes indicates that AI policy, principles and ethics should be improved in representing the heterogeneity of the global community within which AI is adopted while international governance network membership continues to tilt towards experts from developed countries. As a result, the field has no metrics that address underlying problems, not just their symptoms.

The contributions of this paper are threefold. It articulates the four interrelated dimensions of ethical AI adoption in emerging economies and shows how each one shapes the other. It demonstrates that structural differences, and not just magnitude, define the ethical risks in such contexts. And it articulates a mixed methods design for implementing the framework through contextually-relevant metrics.

Analytical Framework

Dimension 1 — Infrastructure and Data Sovereignty

The primary dimension encompasses not only physical connectivity but also the control of data. The material element of this dimension has been established in that infrastructure building is an essential motivator for the deployment of AI technology, although while Western states spent considerable efforts to build sturdy infrastructures, many countries of the Global South have difficulties providing their citizens with stable internet connections, thereby hindering their access to AI technology and preventing them from participating in the global digital economy. The scale element includes the fact that more than half of the world's population lacks access to the internet, and that there are communities without data to use in training any AI model.

The sovereignty element is based on the law. Several countries outside the WEIRD category do not have the necessary regulations and means to regulate data collection, storage, and use, exposing people in such communities to manipulation from corporations and governments in more technologically developed parts of the world. In the current context, the proper regulation of data collection, storage, and use is considered an absolute necessity for ethical AI rather than an afterthought, since without such regulation the conditions of data extraction are dictated unilaterally by the extracting party. Therefore, the proposed framework necessitates that in the process of ethical AI adoption one first establishes the availability of data protection regulations, existence of data on the community in question, and adequate infrastructure for the provision of services.

Finally, the issues of infrastructure and data sovereignty also need to be taken into account from the perspective of the ability of communities to engage in the digital economy in fair and significant ways in the long run. While reliable connectivity creates a platform of opportunities for access to AI-driven services, participation in the digital economy also requires other competencies, such as devices, platforms, computing power, and local data. Communities fully dependent on foreign technologies can find certain limitations in terms of the applicability of applications in regard to their language, culture, economic activities, institutions, and so forth. Therefore, the presence of data of local communities is essential not only in terms of technical relevance of AI systems but also in regard to representation of communities in the process of its development. If local populations have no control over data generated about them, then AI-driven benefits can be extracted from such communities without their participation in decision-making in regard to their own data.

The issue of data sovereignty entails consideration of the institutional mechanisms for managing the process of collecting, storing, processing, exchanging, and using personal and community data. Proper data protection mechanisms should clearly outline responsibilities for organizations and prevent any form of illegal access, extraction, and manipulation of the information. However, legal mechanisms should be combined with mechanisms of enforcement, technical competence, and accessibility for individuals to raise their complaints. It is important to note that such an approach for developing data sovereignty mechanisms should take into account the institutional competence in developing countries and the circumstances of operation of organizations there. Therefore, connectivity sufficiency, data availability, and data protection are interconnected and separate issues that make up the proposed

framework. The community might have access to digital technologies but not be in control of its data or vice versa. Analyzing those issues separately and together can help in identifying the requirements for ethical use of AI.

Dimension 2 — Labour Market and Distributive Effects

The second aspect revolves around the distribution of profits and losses. There are three aspects mentioned here. The capabilities aspect stems from the fact that the use of AI involves heavy investments and only bigger companies have the capability to invest in it. The concentration aspect is derived from industry studies whereby the larger organizations take advantage of AI systems to empower their workforce and smaller organizations depend on technological platforms to experiment. The value capture aspect is derived from the threat faced by developing countries through exploitation of their data and revenues via AI which hampers efforts against financial crimes and corruption.

This aspect also includes the evidence on financial inclusion since it is the most convincing case of an ethical failure leading to a distributive harm. Algorithms for automated decision-making have shown themselves to be biased, have poor ethical governance, and lack transparency of their decision process, resulting in an unjustified outcome and creating more inequalities of access to financial products. These three aspects are considered by the framework independently of each other, meaning that bias is understood as a distributional characteristic, governance – as internal controls, and transparency as contestability. A system can score high in any of them, but fail in others, hence these characteristics cannot be combined into an ethics scores.

Also, the distributive aspect calls for investigation into how economic value associated with AI technologies is generated, controlled, and distributed among companies and workers. Disparities in financial means will affect the capacity of certain firms to use advanced AI technologies, while the degree of market concentration will affect the companies that will own key platforms, data, and technology. This will affect the bargaining powers and the capacity of smaller firms to operate independently within the digital market. Firms that are reliant on other platforms when financing themselves or for using any AI services will lack any control over technological decisions and the economic value they generate. The distributive dimension of AI therefore requires an analysis of how companies adopt AI technologies and the extent of their control over the value generated from such processes.

The criteria should also distinguish between such separate features as bias, internal governance, and transparency because each reflects a different dimension of distributive fairness. While bias means the uneven distribution of results between people or groups of people, the internal governance reflects the internal processes of control that exist within the organization over automated decision-making. On the other hand, transparency is defined as an ability for affected persons to understand the basis of the automated decision-making and to get necessary information to challenge the result. It is also important not to combine all these features into one ethical criterion because an organization can have certain advantages in one sphere and lag behind in another one. For instance, an organization can give explanations regarding automated decisions while providing unfair results, and vice versa. In this regard, maintaining different measures is useful to identify risks of the distributive nature. The mentioned issue is especially relevant to the problem of financial inclusion, where the fairness of automated decisions is associated with their distribution and institutions controlling them.

Dimension 3 — Social Trust and Legitimacy

The third dimension relates to the acceptance by the affected population of the legitimacy of the AI systems, something which has been directly linked by the literature to the performance of the AI in an ethical way: Ensuring the AI performs ethically protects against misuse and facilitates responsible implementation, and tackling biases, fairness, privacy and security enables the stakeholders to be part of the development of AI systems that perform in an ethical manner.

The dimension must also be defined through negation in relation to the failure mode identified in the educational literature. In the case where the technology is viewed as a silver bullet solution to complicated issues, it can lead to greater inequity rather than decreased inequity. This pattern of techno solutionism is also found in AI-based financial inclusion and public services provision and is characterized by a trend of high adoption, low benefits, and trust decline which ultimately hampers beneficial uses. As most of the research on AI tends to consider it more in terms of being a solution rather than a technology within a system of power, policies, and inequality, the issues of who gains, who loses, and whose knowledge gets validated are rarely addressed. The dimension thus calls for the distribution of both benefits and harms to be quantified across differential groups and in terms of the root causes, not symptoms.

Social trust and legitimacy are also needed to be studied from the perspective of individuals and communities who are utilizing the AI-enabled service systems. The degree of trust depends on whether users perceive the system as fair, secure, understandable, and adequately responding to any issues. Such perceptions may vary depending on the type

of the service, institutional context, and risks posed by the automated decisions. For instance, the set of concerns related to an AI-enabled learning platform would be different from concerns related to automated decision-making in finance or government services. Thus, trust cannot be studied only as the extent of people's acceptance of digital technologies. It is also needed to be investigated from the perspective of users' perception of outcome fairness, security, and the possibility for affected users to challenge automated decisions.

Moreover, the legitimacy of AI technologies also depends on how much their development and deployment takes into account the real needs of a community, instead of the assumption that technology will somehow solve all complicated societal issues. In such cases, where organizations implement AI without taking into account the existing deficiencies in local infrastructure, institution-building, and inequalities, the services provided may offer minimal value in spite of the significant degree of adoption among the people. This may lead to the development of a situation when the availability of the technology grows while the level of public trust drops due to unresolved issues. The framework under consideration suggests focusing on the need to assess both the advantages and the drawbacks that various population groups face. In particular, it means understanding if there were any improvements in the accessibility of services, if some groups of people were not included, and if automation created any new difficulties for people.

Dimension 4 — Governance and Regulatory Capacity

The fourth dimension is about the ability to control. The legislative dimension can be understood based on the premise that the proposal of AI Act and GDPR have been made in an attempt to counter unethical use of data and AI in the West, and emerging economies would require developing legislative frameworks for promoting ethical use and the recommendation that regulatory frameworks will ensure the moral use of technology in southern economies.

The enforcement dimension is derived from the proposal of regulations for AI developers and coders, where compliance would be determined through the process of algorithm auditing, with governance frameworks being required to make a contribution towards the Sustainable Development Goals. There are two dimensions to this proposal that warrant particular attention. First, verification would occur at the level of the developer through auditing, and not at the level of the user through disclosures. Second, development impact would become an important criterion for governance legitimacy.

Another perspective that can be applied when discussing the importance of governance and regulatory capacity is the link between the development of legislation on one hand and the actual ability to control AI activities on the other. New nations may need regulatory frameworks dealing with data protection, automated decision-making, algorithmic accountability, and the responsibilities of developers based on the specifics of the institutional and socioeconomic situation in the country. Such frameworks cannot imply the direct import of legislation models developed in technologically advanced countries without taking into account the differences in resources for enforcement, legal systems, markets, and needs of communities. However, some international practices can serve as useful references whereas particular institutions will define what provisions are relevant for their situations. Besides, the rights of the people who make automated decisions and the obligations of organizations collecting and processing personal data should be discussed as well.

External representation, in turn, expands governance even further beyond national regulations as it looks at the inclusion of emerging economies in international standardization and assessment practices related to AI technologies. AI technologies typically transcend national borders through global platforms and data exchanges, meaning that international cooperation is required in order to set common expectations. Yet, international governance practices can be incomplete when they do not take into account the experience and knowledge of developing economies. In this sense, participation needs to go beyond mere membership and to give opportunities to local experts, scientists, policy makers, and community stakeholders to shape the process of creating international standards and assessment practices. Algorithmic auditing could serve as one mechanism of doing so by focusing on the obligations of developers. At the same time, participation in international networks would allow for consideration of different socio-economic environments during the discussion of AI governance.

The external representation module seeks to bridge the gap of participation. Since artificial intelligence systems are global products that are built in one place and used in another, it makes sense to establish a global coalition for AI standardization and assessment. Currently, there are no adequate structures because the composition of international networks is still uneven, and AI working group experts continue to be selected only from developed countries, whereas developing countries have been excluded from the AI life cycle due to the fact that global private companies and developed countries are primarily responsible for the design, development, deployment, and use of artificial intelligence systems. The relatively small mention of populations in the Global South in 463 documents analyzed in relation to 11 anchor terms and more than 60 codes also reflects such participation deficiency (Table 1).

Table 1: Framework Dimensions, Components, and Grounding Evidence

Dimension	Components	Grounding evidence
1 Infrastructure and Data Sovereignty	Connectivity sufficiency; data availability; enforceable data protection	Reliable internet access gaps restricting participation; over half of world population without internet access and communities without training data; absence of legal frameworks and resources to regulate data collection, storage, and use
2 Labour Market and Distributive Effects	Firm capability; market concentration; value capture	Substantial investment requirements disadvantaging smaller organisations; smaller firms dependent on platform funding; AI used to harvest data and profits threatening anti-corruption progress; bias, absent governance, and limited transparency amplifying unequal access to finance
3 Social Trust and Legitimacy	Fairness; privacy and security; contestability	Ethical practice as safeguard against misuse and basis of trust; risk of widened inequity under techno-solutionist framing; unexamined questions of who benefits and who is marginalised; root-cause measures needed
4 Governance and Regulatory Capacity	Legislative development; algorithmic auditing; participation in standards	Need to develop legislative frameworks rather than import them; auditing as verification and SDG benefit as governance requirement; global alliance for AI standardisation and rating; skewed participation in international networks and exclusion from the AI lifecycle

Methodology and Research Agenda

Research Design

A sequential mixed methods approach, involving comparative policy analysis, sectoral adoption survey, and stakeholder consultation, will be adopted. The proposed methodology will address the need to take context-based approaches towards understanding the underlying factors responsible for the digital divide, rather than the symptoms thereof, through working together with governmental, civil society, nongovernmental, and community partners. This will also address the identified need to formulate specific recommendations for policymakers, academia, entrepreneurs, and nongovernmental organizations.

The suggested sequential mixed methods research design may serve as a systematic approach for analyzing connections between the variables of infrastructure, data sovereignty, distributive impacts, social trust and governance capacity. The research starts from comparative policy analysis to study the institutional and legislative prerequisites for the adoption of AI technologies in the selected developing countries. The sectoral adoption survey is supposed to reveal dissimilarities in technology investments, organizational capacity and platform dependency among firms of various sizes. In addition, stakeholder deliberation is included in order to consider the perspectives of individuals and organizations concerned about AI systems. Distributional auditing will help in determining how the advantages and disadvantages of AI adoption are distributed among diverse population groups. Such a sequential design is especially important since the suggested framework implies that ethical risks arise due to the interaction of various structural features rather than single technology-related one.

In addition, the research design takes into account the significance of choosing the criteria that would help to address the reasons behind digital inequality rather than using the general indicators of technology usage. For instance, the presence of an artificial intelligence program in the firm shows that the firm is using technology but does not give any insights whether there is sufficient knowledge about the technology among employees, whether data regulation exists and whether the results obtained from the system are fair. The same is applicable to the abundance of digital service accessibility – it does not prove that people will have an opportunity to use services in a cost-effective manner and in a convenient way for them. Therefore, the proposed method will combine the information related to the policy, firm and community levels and will show a more comprehensive picture of artificial intelligence adoption. In addition, collaboration with government bodies, NGOs and other community players will help to define the locally relevant indicators.

Phase 2 — Comparative Policy Analysis

Policy analysis needs to involve comparison of the legislative frameworks on data protection, algorithmic accountability, and automated decision-making systems among the sampled economies, comparing these frameworks against the tools used to set the standards of ethical AI in rich economies, namely the EU's proposed AI Act and the

GDPR of 2018, without necessarily using the said instruments as templates because the goal is to have legislative frameworks that work within the context of each economy. It is equally necessary to examine whether the legislative frameworks provide for mandatory algorithmic auditing, based on the proposal to ensure compliance through this practice.

The comparative analysis of policies should also focus on the degree to which the legislative provisions ensure the practical protection of people and communities concerned with decisions based on AI technologies. The comparison may include an assessment of the presence of any regulations concerning the duties of data controllers, developers of the technology, service providers, and organizations applying automated systems. Special attention may be paid to the presence of clauses related to data protection, the right to give or withhold informed consent, data sharing, algorithmic accountability, and the right of affected people to receive an explanation or dispute the decision. It is essential to pay attention to the presence of institutional capacities to implement and enforce such regulations. The legislative framework may include many provisions on paper, but they will not be effective if the relevant institutions have no resources to monitor compliance.

Moreover, the other aspect of a comparative analysis would be to consider the appropriateness of a regulatory approach to different economic and institutional settings. The provisions of the EU AI Act and GDPR may be helpful in the context of international trends in regulating the use of AI technologies and protecting personal data, but they should not necessarily be considered as universally applicable templates. Legal, economic, infrastructural, institutional, and market differences may determine the feasibility of adopting certain regulatory requirements in developing countries. Thus, the analysis should reveal both the common principles and the context-dependent regulatory requirements that might have to be reflected in domestic laws. Moreover, the analysis should show whether algorithmic auditing is obligatory, what institutions are supposed to carry out or control auditing, and whether it is possible to take corrective measures on the basis of the audit results.

Phase 3 — Sectoral Adoption Survey

The surveys must be stratified in terms of the size of the business to measure the capability and concentration of resources. The pattern of the study reveals that larger firms have the resources to invest in AI technology whereas small firms do not have such capacity, as well as larger mainstream firms utilize AI systems for their employees whereas small firms rely on the funding from the technology platforms to conduct experiments. Thus, the questionnaire will include questions on the threshold of investments made, the sources of financing, and the reliance on the platform financing in addition to the question on the adoption of AI.

Sectoral adoption survey is expected to help us obtain a more thorough idea about the differences in the adoption of AI technologies between organizations that operate on different scales. Stratification by the scale of the business is especially important, since large companies and small enterprises can differ in terms of financial resources, technical capabilities, and human capital significantly. With the help of this survey, it will be possible to evaluate whether companies have adopted some AI technologies, what kinds of software they use, how much money does it cost and what kinds of organizational processes can be supported by these technologies. Also, it will be possible to evaluate the presence of technical expertise in the organization, its access to digital infrastructure and the dependence on external platforms for the adoption of AI technologies.

The questionnaire also needs to establish whether the organizations finance and control their AI applications on their own, or use platform-based services and other forms of outside financial arrangements. This issue is relevant since the source of technology financing might affect the independence of the organization and its decision-making concerning data, architecture of systems and service provision. Questions regarding investment limits, sources of financing, dependence on the platforms, training of employees, and usage of outside AI providers might be helpful in detecting the differences. Moreover, the questionnaire could address whether the small organizations face any problems with accessing appropriate technical support and setting the terms of service provision. These questions would enable gaining a better insight into the degree of market concentration and value capture. The collected information would enable the distribution aspect of the framework to detect the conditions affecting the benefit that the organizations get from implementing AI.

Phase 4 — Stakeholder Deliberation

Deliberations of this kind must include the categories of stakeholders that have been noted by the literature as indispensable collaborators in this process: governmental, civil society, non-governmental organizations, and community stakeholders. Such deliberations will serve to generate legitimacy judgments and to recognize any gaps in contestability, namely, the capability of those who are impacted to understand and dispute the automated decision, as

recognized in the financial inclusion literature as limited but crucial. There is a reason for deliberations of this type in relation to the lack of representation discussed in the corpus of policies: as the existing policy frameworks must more adequately reflect the diversity of the communities within which AI is used, so deliberations will bring to light where such frameworks fall short ethically.

Stakeholder dialogue should provide an opportunity for various stakeholders to debate on the implications of adopting AI technology and whether the current governance structures appropriately reflect their needs. The representatives from the government can explain their priorities and constraints in terms of regulations, while the civil society organizations and NGOs will be able to add insight regarding community needs, digital divide and the implications of automation. Representatives from business and technology developers can present their views on the costs of implementation, constraints, and requirements. Community representatives can speak about the challenges faced while using the AI-powered services and instances where the automation is creating challenges. Such discussions can allow identifying any possible discrepancies between the interests of AI developers and the needs of those who use these solutions. At the same time, some problems may become obvious that otherwise could have remained unnoticed in policies and organizational assessments. Thus, stakeholder dialogue can serve as a bridge between the theoretical model and the realities of the community where AI technologies are being used.

Moreover, the deliberative process should assess the extent of availability of contestation procedures as well as the ability of affected persons to comprehend and contest decisions that are made automatically by machines. For instance, participants could be asked to reflect on whether the organizations ensure that they provide sufficient explanation, complaints process, and human review in cases where decisions made by AI machines lead to adverse outcomes. Discussions could go further to find out if the users have an understanding of how their data is collected and how they are able to express concerns regarding the use of their data. Such aspects are especially important in a situation where digital literacy and awareness may vary among the different population groups. In addition, there is also a possibility to identify possible inconsistencies between formalized ethical commitments of organizations and the experiences of service users.

Phase 5 — Distributional Audit

These measures account for how benefits and risks are distributed and borne by the different sets of individuals, reflecting the insight that structural inequalities related to connectivity, costs, and literacy have led to marginalised communities being left out of access to education, healthcare, economic opportunities, and citizenship With over 700 million people, that is one-tenth of the global population, living in abject poverty and with a widening disparity in access to digital technologies like mobile telephony and broadband between high and low human development countries, the audit must provide figures separately for connectivity and cost distribution and not simply adoption figures.

Rather than looking at the adoption rate of AI, the distributional audit needs to investigate how the benefits and risks associated with AI adoption are distributed among various socioeconomic groups in the region. Factors such as varying levels of connectivity, cost of service, digital literacy, and access to appropriate devices may affect the ability of people to enjoy the benefits of AI-based services. In this regard, the audit needs to focus on the geographic distribution of these factors among different groups in the population. Furthermore, it is important to analyze whether the application of AI technology increases the access to services in the areas of education, health care, financial services, job opportunities, and public administration. Moreover, the audit should look for populations that find themselves excluded or facing new obstacles due to the deployment of digital services.

The audit needs to further explore the potential for the unequal sharing of risks associated with economic and technological benefits. This implies that there could be communities which will contribute a lot of personal or behavioral data without getting any equal benefit in return from the development of the artificial intelligence services. In addition, some individuals will be disadvantaged through automatic decisions but without having any adequate means of contesting the decision made against them. Therefore, the distributional assessment should not only analyze the allocation of benefits and the occurrence of harm, but also the available correction measures within the various groups involved. Costs of connectivity and service provision should be analyzed separately from adoption since high rates of adoption may hide the differences in cost and access levels. The audit can further assess whether small businesses and disadvantaged communities have enough chance to participate in economic activities related to artificial intelligence.

Evaluation Dimensions

Table 2: Evaluation Dimensions and Candidate Indicators

Dimension	Indicator focus	Grounding rationale
Infrastructure sufficiency	Reliable internet access coverage; service reach across regions	Reliable access gaps restricting participation in the digital economy
Data sovereignty	Existence and enforceability of data protection provisions	Absence of legal frameworks and resources to regulate data collection, storage, and use
Firm capability and concentration	Capital requirements for adoption; share of smaller firms adopting; platform funding dependence	Substantial investment requirements disadvantaging smaller organisations; platform funding dependence
Financial inclusion fairness	Bias incidence; governance controls; transparency and contestability of automated decisions	Documented bias, absent ethical governance, and limited transparency amplifying unequal access to finance
Trust and legitimacy	Perceived fairness; privacy and security confidence; perceived benefit distribution	Ethical practice as safeguard against misuse and basis of trust; unexamined questions of who benefits
Regulatory and auditing capacity	Legislative provisions; auditing requirements; standards participation	Need to develop legislative frameworks; auditing as verification; skewed participation in international networks

Discussion and Implications

Three arguments follow from the framework.

First, the issue of ethical risks in emerging economies is structurally different, not just more. The academic research demonstrates that AI technologies developed in the Global North might be non-compatible with the ethical frameworks in the Global South, and, consequently, the solution oriented on the Global North cannot meet all promises and goals of the AI for Good mission. Also, the academic research proves that the key tools of regulation were elaborated with the purpose to prevent the unethical application of AI technologies in the West, while the emerging economies should develop their own framework. In the case where the framework is inappropriate and lacks the local legislation, no effort to increase compliance will ensure ethical outcome. That is why the proposed framework considers legislative development as the constitutive component rather than the component of compliance and the development of appropriate frameworks as the process of construction rather than adoption (Table 2).

Second, exclusion from the AI life cycle produces harm via methods undetected by metrics of adoption. Developing countries have been excluded from the AI life cycle considering the dominance of global private companies and developed countries in the design, development, deployment, and adoption of AI, and the difference between what could be achieved in terms of AI contribution to social welfare and what is being achieved through actual action related to AI has increased, rather than decreased, because of technological advancements. At the same time, populations in developing nations, where there is ineffective data governance, are exposed to the risk of exploitation by multinationals and governments of technologically more advanced countries. Involvement of AI in gathering data and profits poses threats to the goals of poverty alleviation and sustainable development. Increased adoption may co-exist with increased extraction; that is why the framework demands that data sovereignty and value capture be measured independent of adoption rate. Lack of data about a population makes it even worse: in cases where big populations do not have data to train any AI algorithm, under-representation becomes a structural aspect of the technology infrastructure.

Third, trust is a consequence of visible action, and it is being used up right now. Tackling bias, ensuring fairness, and valuing privacy and security are the tools used by the stakeholders to produce AI systems that meet ethical standards and affect society in a good way. When such tools are lacking, the evidence shows there is bias and inequality in terms of access to finance, and when the technology is advertised as a simple and flawless solution to difficult issues, the consequence could be more inequality rather than less. The danger here is one of a sequence trap: initial use cases that erode trust limit the policy space of later use cases that would have succeeded, which then leads to a stronger call for preemptive regulation than remediation. The suggestion that AI governance frameworks have to show how their impact SDGs is through algorithmic auditing.

Four groups of implications are generated. For policy makers in emerging countries, the framework assists in designing legislation frameworks appropriate to context as opposed to borrowing instruments from other contexts, and implementing algorithmic auditing as the verification tool, and also building capacity in enforcing data protection, as without such an enforcement, populations will be vulnerable to attacks. Focusing on developing appropriate measures to deal with the core issues as opposed to dealing with the symptoms, through working with all relevant governmental and non-governmental stakeholders, is the implementation implication. For the international community, the evidence supports the creation of a global coalition to ensure the standardization and rating of AI because AI systems are of global scope but regulated unilaterally by nations, and also fixing the participation imbalance that makes developing countries underrepresented in the networks of trustable and responsible AI. For organizations and developers, the need is for fairness, privacy, and security to be seen as verified properties, not just designs; and to understand that the high-capital adoption dynamics discriminate against small companies in the marketplaces that they operate in . For researchers, the task is to fill in the gaps in evidence regarding these sectors, and to develop indicators of cause, not effect.

Limitations

This model is an analytical one and has not been empirically verified; the dimensions that this framework posits are suggested for empirical validation but not put forward as findings. The model relies on a review and policy level data and does not rely on primary field study, which makes it difficult to measure the interactions between the dimensions. Furthermore, heterogeneous economies have been used in one category although the degree of difference among the countries in terms of their infrastructure, maturity of law, and market structure is significant — the dependence of small organizations on platform financing and differing capacities of investments at the firm level suggest that heterogeneity within countries could be as significant as heterogeneity across countries. Lastly, the policy corpus analysis that has been conducted using 463 documents evaluated according to 11 anchor terms and over 60 codes is a reflection of guidelines and not enforcement.

The weaknesses inherent in the suggested theoretical model also show some of the areas that need to be given due thought when conducting empirical research in the future. As it is purely conceptual, the links among the four dimensions of the model have yet to be quantitatively tested for their accuracy. Even though the model brings out some of the relationships that may exist between the variables (infrastructure, data sovereignty, distributive impacts, social trust, and governance capacity), the nature of the relationship may be varied depending on the country, sector, and institutional setting. This is because the effects of any of the relationships will be dependent on various contextual factors. For instance, the effect of infrastructural challenges on the uptake of AI will vary depending on access to digital public services, level of development of businesses locally, and the adequacy of government intervention.

Conclusion

Adoption of artificial intelligence technologies in developing countries proceeds at a faster pace than the development of ethics and regulations to regulate them. In this paper, we have stated that the resulting gap is not a generic one, which can be filled through importing the ethical templates from developed nations, but is a unique situation altogether. The ethical framework developed for the situation at hand is not appropriate because it was designed for an altogether different situation; AI technologies developed for the North might not be compatible with the ethical framework used in the South. Additionally, developing countries are left out of the AI lifecycle and the international governance regime, and people living in economies without effective data protection face exploitation from the more advanced countries.

The framework suggested above categorizes this phenomenon into four interrelated dimensions: infrastructure and data sovereignty, labour market and distributional consequences, trust and legitimacy, and governance and regulatory capabilities. The key contribution of the framework offered is seeing them as one system rather than four different bodies of literature. Infrastructure defines what is possible. Data sovereignty defines on whose terms. Distributional arrangements define who gains and who loses. Trust defines if adoption is sustained. Governance defines if any of the other three is constrained. Taking into consideration that the existing literature suggests the tendency for the difference between the contributions AI could make and the social benefit it brings to increase rather than decrease, the framework makes its own statement – that measuring adoption is measuring the wrong variable.

The agenda presented here is both empirical and institutional. It entails comparative research on legislation and audits, firm-level metrics differentiated by size to account for concentration effects, discussion to highlight when prevailing ethical frameworks do not apply within the local context, and distributive auditing which calculates impact (both benefit and harm) among the same communities rather than adoption numbers. The inclusiveness of the AI for social

good will be determined by whether the governance frameworks overseeing the international deployment of AI become truly reflective of the communities these systems serve. So far, there is no indication that this will be the case.

The conclusion underscores the need for responsible adoption of AI in developing economies by shifting focus from a narrow approach to one that takes into account institutional readiness, economic distribution, and community engagement. While the increasing availability of AI technologies can lead to greater efficiency, innovative services, and economic growth, these cannot be deemed as inclusive without the community having the necessary infrastructure, skills, data protection, and governance structures that allow them to take advantage of such opportunities. Through the proposed framework, one is able to understand that the adoption of AI technologies needs to be analyzed based on the context in which they are being created, introduced, and managed. Through its four key dimensions, the framework helps us understand the link between infrastructure and technological participation, data sovereignty and control of information, distribution and allocation of benefits, as well as trust and governance.

The future research agenda is related to validation of the framework dimensions through comparative analysis that will account for the distinctions in national institutions, industrial structure, and community needs. The empirical analysis may reveal whether the suggested criteria are sufficiently capable of reflecting the linkages between the presence of infrastructural resources, regulation of data, market structure, trust, and regulatory capacity. Future research can analyze the way the economic and social outcomes of AI adoption affect small businesses, employees, and underrepresented communities. Comparative study of policies may help to understand which approaches to legislation are adequate for specific institutional environments, and distributional audit will shed light on the distribution of benefits and risks among certain population segments. Finally, international collaboration in research in AI should allow researchers from developing countries to become participants in the process of development of criteria and methods of assessment of AI.

References

Aderibigbe, A. O., Ohenhen, P. E., Nwaobia, N. K., Gidiagba, J. O., & Ani, E. C. (2023). Artificial intelligence in developing countries: Bridging the gap between potential and implementation. *Computer Science & IT Research Journal*, *4*(3), 185-199. 10.51594/csitrj.v4i3.629

Borines, V. A., Turi, A. N., & Hedru, P. (2024, December). The what, so what, and what now of the AI landscape in emerging economies. In *TENCON 2024-2024 IEEE Region 10 Conference (TENCON)* (pp. 804-809). IEEE. 10.1109/tencon61640.2024.10902844

Bulathwela, S., Pérez-Ortiz, M., Holloway, C., Cukurova, M., & Shawe-Taylor, J. (2024). Artificial intelligence alone will not democratise education: On educational inequality, techno-solutionism and inclusive tools. *Sustainability*, *16*(2), 781. 10.3390/su16020781

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., ... & Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International journal of information management*, *57*, 101994. 10.1016/j.ijinfomgt.2019.08.002

De-Lima-Santos, M. F., Yeung, W. N., & Dodds, T. (2025). Guiding the way: A comprehensive examination of AI guidelines in global media. *AI & SOCIETY*, *40*(4), 2585-2603. 10.1007/s00146-024-01973-5

Moon, M. J. (2023). Searching for inclusive artificial intelligence for social good: Participatory governance and policy recommendations for making AI more inclusive and benign for society. *Public Administration Review*, *83*(6), 1496-1505. 10.1111/puar.13648

Roche, C., Wall, P. J., & Lewis, D. (2023). Ethics and diversity in artificial intelligence policies, strategies and initiatives. *AI and Ethics*, *3*(4), 1095-1115. 10.1007/s43681-022-00218-9

Raihan, M. M., Subroto, S., Chowdhury, N., Koch, K., Ruttan, E., & Turin, T. C. (2025). Dimensions and barriers for digital (in) equity and digital divide: A systematic integrative review. *Digital Transformation and Society*, *4*(2), 111-127. 10.1108/dts-04-2024-0054

Sarma, M., Senaratne, C., & Matheus, T. (2023). Challenges and opportunities of ethical AI and digital technology use in emerging economies. *Elgar companion to regulating AI and big data in emerging economies*, 42-58. 10.4337/9781785362408.00008

Truby, J. (2020). Governing artificial intelligence to benefit the UN sustainable development goals. *Sustainable Development*, *28*(4), 946-959. 10.1002/sd.2048