SPIDER
EU-LAC Digital Partnership

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WG1: HUMAN-CENTRIC DIGITAL TRANSFORMATION

TOPIC 1.1: Reimagining Public Services: Putting Citizens First in the Digital Era

The discussion highlighted the central role of civil servants in driving citizen-focused digital transformation when equipped with the right skills, autonomy, and technological infrastructure. Experiences such as Estonia showed that embedding IT specialists within public institutions and fostering a culture of trust in e-governance enables civil servants to co-design and implement services effectively, strengthening institutional capacity and public trust.

Creating spaces for co-creation and collaborative governance was seen as essential, allowing civil servants to work with startups, researchers, and citizens to test innovative solutions beyond traditional hierarchical structures. This promotes interinstitutional collaboration, better service provision, and participatory policy-making.

Transparency, accountability, and citizen engagement were emphasized as critical, particularly in AI-enabled services. High-risk AI systems should include human oversight, diverse and representative datasets, rigorous testing, and ongoing monitoring to prevent bias and protect citizens' rights. Participatory governance and interdisciplinary oversight help ensure fairness and capture societal dimensions often overlooked by technology alone.

Finally, continuous training, ethical frameworks, and institutional recognition are key to sustaining innovation. Public servants need the skills and support to navigate technological, social, and ethical challenges, while clear rules, audits, and public reporting maintain trust and ensure that digital transformation benefits citizens equitably.

How can civil servants, not just policymakers, be empowered as digital transformation agents?

Civil servants can become key actors in digital transformation when they are equipped with the right skills, autonomy, and technological infrastructure. The example of Estonia illustrates how this can be successfully achieved. Through continuous investment in digital literacy, interoperable systems, and a culture of trust in e-governance, Estonian civil servants have played a central role in both designing and implementing public digital services. Rather than outsourcing reforms, they were involved in building and maintaining core infrastructures such as the X-Road data exchange system[1] and the national e-identity framework[2]. Embedding IT specialists within public institutions and encouraging agile experimentation allowed them to adapt quickly, ensure interoperability, and strengthen public trust.

In contrast, other countries, such as Greece, have relied more on partnerships with big tech companies to modernise their public administration. While this approach has helped accelerate implementation, it also highlights the importance of ensuring that public servants remain central to the process through training, co-design roles, and knowledge transfer. Otherwise, digital transformation risks weakening long-term public-sector capacity and sovereignty.

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[1] https://e-estonia.com/solutions/interoperability-services/x-road/
[2] https://e-estonia.com/solutions/estonian-e-identity/id-card/

During the participants' discussion, creating spaces for co-creation and collaborative governance was seen as essential. Through approaches such as pre-commercial procurement and participatory design, civil servants can work alongside startups, researchers, and citizens to propose innovative solutions beyond traditional hierarchical structures. This demands a rethinking of service provision, data management, and identity systems, building on interoperable infrastructures that allow the reuse of data across institutions. Civil servants play a key role in organising and overseeing these processes, contributing to data generation and stewardship while ensuring that participatory mechanisms are embedded in public policy design. Co-creation of digital services should involve the entire ecosystem: citizens, policymakers, and public servants alike, promoting interinstitutional collaboration, shared responsibility for innovation and trust.

Transparency, accountability and citizen trust were also highlighted as critical elements. Public scrutiny and the ability to challenge or appeal digital decisions are central to a citizen-focused digitalisation process. Civil servants must safeguard transparency and actively engage citizens in discussions about how digital systems are designed and used. This involves promoting open data practices that enable evidence-based decision-making and public oversight. By becoming promoters of good practices and advocates for openness, civil servants can help ensure that digital transformation strengthens democratic accountability rather than diminishing it.

Participants also emphasized the importance of changing mindsets and fostering a culture of innovation. Digital transformation is not just about deploying new applications or automating processes. It also requires a cultural shift among public servants. Too often, digital tools are designed without considering how civil servants interact with them, leading to a loss of human connection and engagement. Institutional recognition and distributed leadership are therefore key: every public servant should feel that their daily work directly contributes to innovation and the creation of public value. Encouraging experimentation, feedback, and collaborative problem-solving can foster a culture of innovation across the public sector.

Continuous training and capacity building were identified as key enablers of long-term success. To sustain transformation, continuous training in digital skills, data literacy, and citizen-centered design is essential. Public servants must be equipped not only to use digital tools effectively but also to critically understand their social and ethical implications. Investing in lifelong learning and professional development ensures that the public sector remains agile, competent, and capable of shaping digitalisation in line with public interest.

Specific regional challenges were also identified:

- In the EU, a lack of interoperability between ministries and siloed platforms limits data sharing and coordinated service delivery. An ageing population may also struggle to adopt digital services. However, the relatively small size of many countries and generally advanced infrastructures can facilitate the replication of successful models such as Estonia's, although islands and remote areas still face connectivity challenges.
- In Costa Rica, the development of a digital health system has unified medical records, and there is also a digital platform that integrates social security information, personal appointments, clinical data, and pension details. However, access is limited to those with internet connectivity and mobile devices, which can create new forms of exclusion.

- In Mexico, a national ID number enables access to public services, but the absence of a unified platform across states and municipalities, combined with political changes and limited financial resources, has hindered the implementation of a long-term, coordinated strategy.

How to ensure AI in citizen-facing services does not reinforce bias?

At the EU level, the AI Act adopts a risk-based approach, categorising AI systems as minimal, limited, high-risk, or unacceptable. For "limited risk" systems, such as many chatbots or content-generating tools, transparency obligations apply to support accountability. For example, users must be informed that they are interacting with an AI system. In contrast, high-risk systems (which may include citizen-facing public services affecting rights or legal status) are subject to much stricter requirements. These include human oversight, robust data governance, bias mitigation measures, documentation, and traceability, all designed to ensure that AI strengthens public services without undermining rights or non-discrimination. Conformity assessments are also required, ensuring that datasets are diverse, systems are explainable, and humans remain actively in the loop.

Bias mitigation under the AI Act is explicitly regulated through Article 10, which obliges providers of high-risk AI systems to use training, validation, and testing datasets that are relevant, sufficiently representative, and as free of errors as possible given the intended purpose. Datasets must account for the persons or groups on which the AI system will be applied, including specific contextual, behavioural, or functional settings. Providers are required to implement appropriate measures to detect, prevent, and mitigate any biases identified. In exceptional cases, Article 10(5) allows the processing of special categories of personal data specifically to ensure bias detection and correction.

Article 15 of the AI Act further strengthens bias prevention by requiring that high-risk AI systems be designed and developed to reduce biased outputs, including technical and organisational measures to address feedback loops and errors. These measures ensure that systems perform consistently, safely, and without systematically disadvantaging any group. In addition, ongoing monitoring and thorough documentation are mandatory. Providers and deployers must maintain logs and traceability of datasets, decisions, and system performance so that any bias-related issues can be identified, audited, and corrected. Post-deployment monitoring is also required to detect drift, errors, feedback loops, or discriminatory outcomes.

During the discussion, participants emphasized the importance of transparency and human oversight, ensuring that AI in citizen-facing services does not reinforce bias starts with transparency and accountability. A human-in-the-loop approach is essential, as public servants must remain actively involved in AI-supported decision-making processes. Citizens should understand how automated decisions are made and which foundation models power chatbots and other AI tools. This openness builds public trust and allows users to challenge or appeal outcomes, fostering a culture of accountability in digital public services.

Building on transparency, bias prevention must also begin at the design stage. Training datasets need to be diverse and representative so that all social groups are fairly represented and structural discrimination is avoided. AI systems should undergo thorough impact assessments and exhaustive testing before deployment to detect and correct potential biases. Regular algorithmic audits ensure fairness, explainability, and accuracy over time. Rather than relying on continuous online adaptive learning which can unintentionally embed biases, AI tools should collect user feedback and update offline, integrating new data only after verifying that it is unbiased and reliable.

Effective oversight further requires interdisciplinary collaboration. Teams combining technologists, social scientists, ethicists, and public servants are best positioned to address both technical and societal dimensions of bias. In parallel, participatory governance that actively engages citizens and civil society organisations in the design and evaluation of AI tools creates shared responsibility. This inclusive approach helps to uncover real-world impacts that might otherwise be overlooked, ensuring that the systems serve the public fairly and accountably.

Finally, these operational and participatory measures need to be supported by strong ethical and regulatory frameworks. Clear rules, transparency on model design and decision-making, regular audits for bias, and public reporting are necessary to institutionalise fairness in AI systems. Even in contexts with limited digital infrastructure or computing capacity, such as in some regions of Mexico, public confidence can be reinforced through consistent human oversight and ongoing communication about governance practices. As private-sector and civil society initiatives mature, their integration into public systems should adhere to principles of accountability, inclusivity, and responsible innovation, ensuring AI benefits all citizens equitably.

TOPIC 1.2: AgriTech for the People: Satellite and AI Innovations

Earth Observation (EO) data and AI are transforming agriculture, but their impact depends on translating, adapting, and democratizing access. In Europe, initiatives like the Copernicus Programme provide open, standardized satellite data, which combined with in-field sensors and AI models, support precision agriculture, optimize irrigation, and improve crop management. Farmers often rely on cooperatives, public platforms, or NGOs to turn complex data into actionable insights. In Latin America, local adaptation and grassroots experimentation demonstrate the importance of tailoring technologies to regional conditions and community needs.

Practical applications show wide-ranging innovation: AI-driven crop disease detection, smart irrigation, and optimized harvesting in Europe, and irrigation efficiency, soil monitoring, and deforestation-free certification in Latin America. These tools enhance productivity, sustainability, and supply chain traceability, while local calibration ensures global technologies meet local agricultural realities.

Governments, cooperatives, and local organizations are crucial for enabling access and understanding. Open data platforms, funding, training, and participatory approaches help farmers, especially smallholders, translate complex EO and AI information into practical decisions. Intermediaries and cooperative networks further support adoption and knowledge sharing.

Looking forward, Europe's structured frameworks and data infrastructure, combined with Latin America's local innovation and sustainability experience, can create inclusive EO and AI solutions. Joint platforms and international cooperation are key to ensuring these technologies improve productivity, traceability, sustainability, and food security for all farmers.

How are farmers in Europe and LAC already using Earth Observation (EO) data and AI to improve crop management and food security, and what lessons can they share with each other?

The European Union's Copernicus Programme[3] provides free, open, and constantly updated Earth Observation data from the Sentinel satellites. Farmers, researchers, and agribusinesses use this data to monitor soil moisture, crop growth, droughts, and land cover changes. These datasets are the foundation for precision agriculture and climate-smart farming, helping optimize irrigation, fertilizer use, and planting decisions. These data are combined with in-field sensors and AI models to improve field management, crop productivity, and sustainability. Even though Copernicus data are free, intermediaries such as cooperatives, NGOs, or public platforms are often needed to translate the complex data into actionable insights for farmers. Although EO data are freely available, most farmers lack the technical capacity to interpret satellite information, so cooperatives, public agencies, and tech companies act as intermediaries, converting EO data into practical insights, for example weather alerts or irrigation advice. This "translation layer" ensures that data are usable and actionable[4].

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[3] https://www.copernicus.eu/en

[4] https://www.copernicus.eu/en/access-data/dias

In Catalonia (Spain), the Department of Agriculture uses AI-driven drones and satellite imagery to monitor crop conditions and predict harvesting times. Predictive models support irrigation planning and help detect pests and diseases early. Farmers receive remote alerts and water distribution plans, improving resource efficiency and yield stability. In Trentino (Italy), AI and EO data are used to track fruit maturity in vineyards and apple orchards. By identifying the exact moment for harvesting, farms can optimize labor management and reduce food loss, which is particularly relevant for seasonal crops that rely on temporary workers. Farmers in Italy, France, and Spain are also experimenting with computer vision systems that detect early signs of disease on leaves or fruit, helping react quickly to outbreaks and protecting entire harvests.

In Costa Rica, farmers and exporters use satellite monitoring to prove that coffee and pineapple production does not contribute to deforestation, in line with the EU Deforestation Regulation (EUDR). This certification process uses drones, EO imagery, and AI analysis to ensure traceable supply chains[5]. Universities near San José are developing a system that combines humidity and nutrient sensors with AI algorithms to monitor soil quality. Imported sensors from the UK and USA were initially incompatible with local soil, so researchers are now building AI calibration models to adapt data readings to tropical conditions, highlighting the importance of local adaptation of global technology. In Ecuador, there is potential to apply AI virtual assistants and drone mapping for irrigation efficiency, soil classification, and fire prevention, which could enhance resource conservation and climate resilience. Across Latin America, several initiatives aim to use machine learning algorithms to recommend which crops are best suited to local soil and weather conditions, optimizing land use and improving food security.

Participants noted that both regions show strong interest in combining EO and AI to support sustainable farming. Europe offers open-access data frameworks such as Copernicus and strong technical infrastructure, while Latin America demonstrates innovation in local adaptation and community-level experimentation. Future cooperation could focus on calibrating EO tools for tropical environments, building local data platforms, and exchanging training programmes for farmers and agronomists, ensuring that lessons from each region benefit the other.

What role should governments, cooperatives, or local organizations play in helping farmers in both regions access and understand EO data?

Governments have a central role as policy enablers, data integrators, and capacity builders. They can make EO data available through national open platforms, fund public–private partnerships, and include digital agriculture in national strategies. In the EU, the Common Agricultural Policy (CAP) includes incentives for digital transition and precision farming. Similar frameworks could be promoted in LAC through public innovation funds and capacity-building programmes.

Agricultural cooperatives also contribute significantly to enabling access. In Italy, cooperatives act as information hubs, providing weather alerts and pest warnings to their members. By pooling resources, small farms can collectively access EO-based tools that would otherwise be unaffordable

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5 https://www.globalcompliancenews.com/2025/10/02/https-insightplus-bakermckenzie-com-bm-consumer-goods-retail_1-european-union-commission-considering-delaying-eudr-application-for-another-year_09242025/

individually. Similarly, in Costa Rica, farmers often face information overload from EO and weather platforms such as Copernicus, so local institutions or public services translate technical data into practical advice, answering concrete questions like "Is today a good day to plant or irrigate?" or "Should fertilizer be added this week?".

Public funding and expert support further facilitate adoption. Under the Catalan Strategy on AI, small farmers and SMEs can apply for publicly funded assessments with certified AI experts, who identify suitable AI solutions, assess risks, and recommend tools based on the farm's maturity level. This ensures even small producers receive tailored digital advice. Platforms like Belgium's Terrascope[6] act as intermediaries between Copernicus and local farmers, providing ready-made maps and analytics for non-specialists, while Costa Rica's SIMOCUTE[7] integrates satellite data to monitor environmental changes, offering a foundation for agricultural monitoring systems and supporting compliance with regulations such as the EU Deforestation Regulation.

Investment in R&D and dedicated innovation funds is critical, especially in Latin America. In Costa Rica, despite strong electromechanical and engineering research, funding for agritech innovation, blockchain, or AI applications is limited, and small farmers struggle to access financing from national development banks. Governments could design targeted grants or credit lines for digital agriculture to promote EO and AI adoption. Initiatives like the Inter-American Institute for Cooperation on Agriculture (IICA)[8] support start-ups and small companies in EO, drone, and sensor analytics, and collaboration with European partners, such as the SPIDER network, could strengthen technical exchange and build a shared EU–LAC ecosystem for agritech innovation.

Policymakers can also facilitate EO adoption by creating public digital services accessible to all farmers, such as free EO data dashboards customized to national crops, government-backed expert networks offering "AI-readiness assessments," and pilot funding for proof-of-concept projects using EO and AI in small farms. European initiatives like the Agri-Digital Growth project[9] (co-funded under the Interreg Central Europe Programme, 2024–2026) complement agricultural policies by providing training, living labs, and pilot projects to help small and medium-sized farms adopt technologies such as EO, sensors, and AI.

Both regions recognize the need for translation and mediation between complex data and practical farming actions: the EU model of cooperatives and public data services provides a successful blueprint for inclusive access, while Latin America brings grassroots innovation but needs stronger institutional and financial support. Building regional platforms, supported by public funding and international cooperation, can ensure EO data becomes a shared resource for all farmers, large and small.

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[6] https://terrascope.be/en
[7] https://simocute.go.cr
[8] https://iica.int/en/
[9] https://www.interreg-central.eu/projects/agri-digital-growth/

WG2: DIVERSITY, EQUALITY AND INCLUSION (DEI)

TOPIC 2.1: Making multimodal AI work in Spanish and Portuguese

The discussion showed that multimodal AI systems still do not perform with the same quality in Spanish and Portuguese as they do in English, largely due to the lack of diverse and high-quality data. Differences in accuracy, interpretation of cultural nuances, and handling of dialects affect both user experience and the trust of people who rely on these technologies for communication, education, or public services. These limitations are intensified in countries with high linguistic diversity, where models often recognize only dominant variants.

Participants stressed that the gap is not only technical but structural. Uneven connectivity, the concentration of resources in major cities, and limited investment in multilingual models perpetuate an AI ecosystem centered on English and Eurocentric frameworks. At the same time, strict regulatory frameworks make access to multimodal data more difficult, while the lack of algorithmic transparency generates distrust and reinforces existing inequalities.

To close these gaps, the discussion highlighted the need to expand digital infrastructure, diversify training data, and promote the direct participation of local communities in the creation and validation of content. Strengthening ethical governance, as well as collaboration between Europe and Latin America, is essential to accelerate progress toward inclusive and culturally adapted models.

Finally, participants underscored that trust in AI depends on transparent processes, recognition of the labor of those who label data, and digital literacy initiatives that allow citizens to understand, question, and safely use these technologies. Only through these measures can multimodal AI become truly useful and equitable for Spanish and Portuguese speakers.

How effective is current multimodal AI (text, images, video, audio) in supporting Spanish and Portuguese compared to English or other widely used languages?

Multimodal AI tools still show lower accuracy in Spanish and Portuguese compared to English. They often misinterpret idioms, humor, slang, and region-specific expressions, especially in Latin American Spanish and Brazilian Portuguese, and subtitles or transcriptions frequently distort or omit contextual meaning, affecting comprehension and trust in automated outputs. While AI can recognize words correctly, it frequently fails to convey tone, formality, and cultural nuance; for instance, misuse of “Usted” or confusion between European and Brazilian Portuguese reflects a lack of contextual understanding that makes content feel impersonal and detached from local realities. Users also reported that simultaneous translation and voice interaction remain difficult to follow, particularly when switching between dialects, as most AI systems perform best in English and require users of other languages to invest additional time in training or adapting models, creating barriers to participation and discouraging engagement.

In large and linguistically diverse countries such as Brazil, regional varieties are rarely represented in AI training data, leading voice assistants and chatbots to fail to recognize accents or local idioms from outside dominant regions like São Paulo. Over time, this limits inclusivity and reduces the perceived usefulness of AI tools. Most AI models rely on datasets that prioritize English or European Portuguese, creating a Eurocentric bias. Updates and fine-tuning cycles occur faster in English, leaving Spanish and Portuguese users with slower improvements and less reliable results, and the scarcity of high-quality annotated data hinders the creation of robust benchmarks. In sector-specific domains such as healthcare and education, multimodal AI performs adequately for basic classification tasks but struggles with complex interpretation. In medical imaging, for example, systems can detect abnormalities but often misread nuanced pathological patterns due to limited multilingual clinical data. Similar gaps appear in educational platforms, where English resources remain dominant.

Limited linguistic and cultural adaptation reinforces digital inequality. When tools fail to operate effectively in a user's native language, participation in digital environments becomes restricted, widening the digital divide between English-speaking users and communities across Europe and Latin America, where Spanish and Portuguese predominate.

What barriers exist in training multimodal AI systems for Spanish and Portuguese, and how could they be overcome?

<u>Barriers:</u>

The most persistent obstacle in training multimodal AI for Spanish and Portuguese lies in the limited availability of large, diverse, and high-quality multimodal datasets, as existing systems are primarily trained in English. This reduces their performance when processing regional dialects, idiomatic language, or informal expressions, perpetuating systematic bias and limiting cultural adaptability. Socio-economic inequalities further affect access to reliable internet and advanced digital tools, with uneven connectivity across Latin America and parts of the Iberian Peninsula, especially outside major cities. AI resources and research are highly concentrated in metropolitan centers such as São Paulo or Madrid, reinforcing disparities and leaving smaller or rural communities behind. Spanish and Portuguese contain wide varieties of accents, dialects, and cultural registers, but these are often underrepresented in training data, which results in outputs that reflect only dominant linguistic norms and weakens inclusivity.

Insufficient investment and fragmented research efforts hinder the development of multilingual AI systems, and the absence of coordinated public strategies or open data policies leads to duplication and a scarcity of shared resources. Moreover, commercial incentives continue to prioritize English due to its larger market, and ethical or regulatory challenges (such as GDPR constraints on sensitive multimodal data and the opacity of black-box algorithms) further complicate adaptation, reducing user confidence. In addition, the AI value chain depends heavily on low-paid data labelers in developing regions. This unequal distribution of digital labor reinforces global inequalities and contradicts the ethical principles that should underpin inclusive technological development.

AI-generated misinformation and biased outputs can erode public confidence, particularly among younger users. When these tools provide culturally inaccurate or linguistically biased information, users become less likely to trust or engage with them, reducing digital literacy and adoption in the long term.

Ways to overcome barriers:

Overcoming these barriers requires action on multiple fronts. Expanding connectivity and access to digital tools in underserved regions is fundamental for equitable AI development. Investments should target underserved regions to prevent further concentration of resources in large metropolitan areas. Inclusion must begin at the data collection stage, with training datasets that represent the full diversity of dialects, accents, genders, and cultural contexts in Spanish and Portuguese speaking communities, alongside transparent documentation of data sources and methodologies to identify and reduce bias. Local communities, linguistic experts, and cultural institutions should actively participate in data collection and validation. This participatory model ensures that AI systems not only process language accurately but also reflect the lived realities, values, and communication styles of diverse users.

Governments, research centers, and private organizations should pool resources to support open and cooperative AI research initiatives. Funding mechanisms that prioritize multilingualism and cross-regional collaboration can bridge the gap between Europe and Latin America. Responsible AI governance should include fairness audits, transparent communication of system limitations, and robust privacy protections. Ethical oversight mechanisms are essential to guarantee user trust, especially when dealing with personal or sensitive data.

Developing fair working conditions and recognition for data-labeling workers is crucial to making AI development more ethical and sustainable. Improved compensation, visibility, and inclusion of these contributors in the AI ecosystem can reduce systemic inequities. Finally, educational campaigns and capacity-building initiatives can help users understand both the potential and the limitations of AI systems. Transparency about how algorithms function, combined with user training in digital literacy, can restore trust and promote responsible use.

TOPIC 2.2: Building Culturally Sensitive and Inclusive AI across EU & LAC

The discussion emphasized that current AI continues to reflect primarily Western cultural paradigms, which limits its ability to represent the cultural diversity of Europe and Latin America. The lack of culturally specific data, models' tendency to generalize nuances, and the absence of minoritized languages in training datasets result in systems that often fail to capture the symbolic, emotional, or contextual depth of local expressions. Cases such as Ecuador illustrate how these technologies perform particularly poorly in multilingual and Indigenous contexts.

Participants stressed that these limitations are not only technical but also deeply ethical and social. When AI misinterprets cultural context, it risks erasing identities, reinforcing stereotypes, or reproducing existing inequalities. The cultural homogenization produced by many models threatens the value of oral traditions, ancestral knowledge, and the plurality of perspectives. Added to this, is the danger that models may develop reasoning patterns increasingly misaligned with human cultural frameworks.

Despite these risks, there is significant potential for AI to become a tool that preserves and celebrates cultural diversity. Achieving this requires integrating inclusion from the beginning of the design cycle, involving local and Indigenous communities, and developing specialized models capable of reflecting specific languages, values, and cultural practices. The discussion also emphasized the need for governance frameworks that ensure fairness, transparency, and accountability.

Finally, strengthening digital literacy and fostering citizen participation are key conditions for building trust and enabling people to recognize and question AI's cultural biases. With appropriate policies, community engagement, and greater corporate transparency, AI can become an instrument that expands, rather than diminishes, cultural diversity.

To what extent can AI systems today capture and reflect cultural particularities across different European and Latin American societies?

AI models are predominantly trained on data reflecting Western languages, values, and worldviews, which limits their ability to authentically represent diverse cultural realities. Large language models (LLMs) tend to prioritize majority perspectives, smoothing over cultural nuances and regional differences in order to deliver "universal" outputs. As AI becomes more advanced, models may develop internal "languages" or "values" that diverge from human understanding, creating systems that reflect neither local nor global cultures. At the same time, dedicated systems trained on culturally specific datasets can accurately reflect local traditions, expressions, and knowledge systems, offering a pathway to preserve diversity rather than erase it.

Examples such as Ecuador illustrate the limits of current AI in multicultural contexts: in societies with multiple languages, including Kichwa, Shuar, and other Indigenous groups, AI struggles to represent deep relational and symbolic elements of culture, particularly those transmitted through oral traditions. Authentic cultural representation depends on involving communities directly in AI design, supporting underrepresented languages, and adopting ethical and inclusive practices that respect local ways of knowing. Achieving cultural sensitivity requires AI to balance global reach with contextual understanding, ensuring that local cultural frameworks are not overwritten by dominant narratives. Capturing cultural particularities, therefore requires models to move beyond literal interpretation, integrating meaning, emotion, and the social significance behind words and expressions.

What risks arise when AI misinterprets cultural or linguistic variations?

When AI fails to understand cultural or linguistic nuances, it can erase or distort local traditions, undermining the identity and visibility of minority communities. Systems trained on English or Western-centric data often ignore other worldviews, reinforcing the marginalization of non-Western languages and cultural logics. In contexts such as Ecuador, AI may oversimplify or misrepresent ancestral languages, oral traditions, and symbolic ties to nature, leading to the misappropriation or disappearance of cultural heritage.

These shortcomings can also amplify stereotypes embedded in training data, perpetuating discriminatory or reductive portrayals of certain groups or identities. Misinterpretation of linguistic variations can lead to inequitable access to digital tools and discrimination in service delivery, disadvantaging linguistic minorities or culturally distinct populations. Overreliance on standardized AI outputs can further dilute the richness of cultural diversity, producing content that appears globally neutral but lacks authenticity. The prioritization of data-driven objectivity risks undermining traditional knowledge systems essential to many societies.

As models evolve, they may develop internal patterns of reasoning that no longer align with any human cultural framework, making decisions opaque and untraceable. The digital divide deepens when cultural misrepresentation compounds existing social and economic disparities between connected and marginalized groups.

What practical steps and actions can be taken for AI to become culturally sensitive?

Cultural sensitivity should guide every stage of the AI lifecycle, from pre-design to monitoring, ensuring that inclusivity is embedded in system development. This requires including people from diverse cultural, linguistic, gender, and social backgrounds in AI design so that a multiplicity of worldviews and lived experiences inform decisions. AI policies, programs, and regulations should explicitly consider cultural and linguistic pluralism, and also policymakers must recognise diversity as a key dimension of AI governance and enact frameworks that actively counter bias and stereotypes. In this way, frameworks must actively counter bias and stereotypes. Beyond general-purpose models, specialized AI systems can be designed to understand and communicate the values, idioms, and expressions unique to specific cultures.

To move from linguistic translation to cultural and value-based translation, AI must learn to interpret meaning and symbolism, capturing emotional and cultural depth rather than producing literal translations. Data collection practices should be redesigned to localise beyond translation, with curated datasets that respect local contexts, oral traditions and cultural frameworks. Participatory design processes involving local and Indigenous communities ensure that systems reflect the voices and values of those they serve, while integrating Indigenous languages and traditional knowledge systems expands data diversity and preserves underrepresented knowledge, making sure that oral cultures have a digital presence.

Building local capacity for AI development enables communities to design culturally aligned technologies and maintain digital sovereignty. Ensuring ethical data collection, prioritising consent and transparency, together with respecting cultural ownership, avoids extractive or exploitative dynamics. Institutionalizing cultural sensitivity in AI governance frameworks ensures that evaluation, funding, and regulatory processes incorporate these principles. Greater transparency and accountability from technology companies (regarding data origins, algorithmic logic, and cultural assumptions embedded in their designs) is also essential. Finally, users should be empowered to understand cultural bias in AI and to use prompting strategies that highlight their own cultural context.