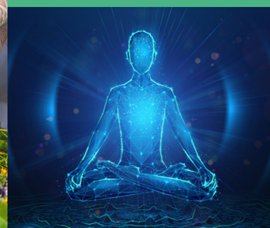




Mapping the application of artificial intelligence in traditional medicine

Technical brief

World Health Organization
ITU
WIPO
WORLD
INTELLECTUAL PROPERTY
ORGANIZATION

Mapping the application of artificial intelligence in traditional medicine

Technical brief

World Health Organization

ITU

WIPO
WORLD
INTELLECTUAL PROPERTY
ORGANIZATION

Mapping the application of artificial intelligence in traditional medicine: technical brief

ISBN (WHO) 978-92-4-010766-3 (electronic version)
ISBN (WHO) 978-92-4-010767-0 (print version)
ISBN (ITU) 978-92-61-39921-4 (electronic version)
ISBN (ITU) 978-92-61-39911-5 (print version)

Suggested citation. Mapping the application of artificial intelligence in traditional medicine: technical brief. Geneva: World Health Organization and International Telecommunication Union, 2025. Licence: CC BY-NC-SA 3.0 IGO.

Cataloguing-in-Publication (CIP) data. CIP data are available at https://iris.who.int/.

Cover photos (left to right, top to bottom rows):

Reaching people at risk of malaria in remote areas of Chhattisgarh, India, 2023 © WHO/Atul Loke

Stock image symbolising the interconnectedness between ecology, sustainability and the medicinal properties of plants © Shutterstock/Billion Photos

Stock image of researcher measuring sapling for botany experiment © Envato/DC Studio

An AI robot specialized in Traditional Chinese Medicine checks a human's pulse at the 2020 China International Fair for Trade in Services in Beijing, China, 2020 © Alamy Stock Photo/Imago

Stock image of a researcher working with medicinal herbs © Envato/Yanadjana

Stock image of an illustration of a human figure sitting in lotus yoga pose symbolising mental health and meditation © Shutterstock/artacet

Contents

Acknowledgements

The development of this document is a collaborative effort between the Department of Digital Health and Innovation (DHI), WHO Global Traditional Medicine Centre (GTMC), and the Traditional, Complementary and Integrative Unit (TCI) under the Department of Integrated Health Systems, as part of the enabling pillar under the Global Initiative on Artificial Intelligence for Health (GI-AI4H). Built on discussions and conceptualization initiated by the topic group on artificial intelligence and Traditional Medicine within the WHO-ITU Focus Group on Artificial Intelligence for Health (FG-AI4H), the document benefits from the knowledge and insights gathered through multi-disciplinary experts from the domains of Traditional Medicine, digital health and artificial intelligence.

The core development team includes Sameer Pujari (DHI), Yu Zhao (DHI), Maki Kajiwara (GTMC), Sungchol Kim (TCI), Jose Eduardo Diaz Mendoza (DHI), Rajeshwari Singh (DHI), Pawan Godatwar (WHO Regional Office for South-East Asia), Qin Liu (TCI), Pradeep Dua (TCI), Geetha Krishnan Gopalakrishna Pillai (GTMC), Lori Mcdougall (The Partnership for Maternal, Newborn & Child Health), Shada Alsalamah (DHI), Kanika Kalra (DHI), Richelle George (DHI), Manjeet Saluja (GTMC) under the guidance of Alain Labrique (Director, DHI), Shyama Kuruvilla (Director a.i. GTMC) and Rudi Eggers (Director, Integrated Health Services).

Partners from United Nations (UN) agencies and governmental representatives also provided valuable contributions throughout the development of this document: Simão Campos (International Telecommunication Union) [ITU]), Nancy Pignataro (World Intellectual Property Organization) [WIPO]), Sara Fuentes Maldonado (WIPO), Fei Jiao (WIPO), Amandeep Singh Gill (UN) and Rajesh Kotecha (Ministry of Ayush, India).

The World Health Organization (WHO) acknowledges the external experts who participated in the technical consultation and contributed to the development of this brief: Hupleka Chabalala (Department of Science and Technology, South Africa), Caio Portella (Brazilian Academic Consortium for Integrative Health, Brazil), Jeremy Y. Ng (University Hospital Tübingen, Germany), Roshanak Ghods (Iran University of Medical Sciences, Islamic Republic of Iran), Kai Siang Lim (Selayang Hospital, Malaysia), Hiba Boujnah (Charité Competence Center for Traditional and Integrative Medicine, Germany), Vijaylaxmi Asthana (Traditional Knowledge Digital Library, India), Deepika Mishra (All India Institute of Medical Sciences, India), Sumeet Goel (Ministry of Ayush, India), Tanuja Manoj Nesari (All India Institute of Ayurveda, India), Anandaraman (All India Institute of Ayurveda, India), Galib R (All India Institute of Ayurveda, India), Meera Bhojani (All India Institute of Ayurveda, India), Shivakumar Harti (All India Institute of Ayurveda, India), Arun Mahapatra (All India Institute of Ayurveda, India), Amrish Dedge (All India Institute of Ayurveda, India), Prashant Gupta (All India Institute of Ayurveda, India), Shifa Shetty P (All India Institute of Ayurveda, India), Nikita Sharma (All India Institute of Ayurveda, India), Arshathjyothi (All India Institute of Ayurveda, India), Karthik KP (All India Institute of Ayurveda, India), Pooja Rani (All India Institute of Ayurveda, India), Athul TP (All India Institute of Ayurveda, India), Anagha (All India Institute of Ayurveda, India), Aishwarya Joglekar (All India Institute of Ayurveda, India), Stefan Germann (Ursimone Wietlisbach Foundation, Switzerland), Nilce Ekadnzi (Centre for International Intellectual Property Studies, France), Pravit Akarasereenont (Center of Applied Thai Traditional Medicine, Thailand), Martha Gissela Haydee Cardoza Moreno (Seguro Social de Salud del Peru (EsSalud), Peru), Beatriz Paulina Ayala Quintanilla (EsSalud, Peru), Kashinath Samgandhi (Morarji Desai National Institute of Yoga, India), Elanchezhiyan Devarajan (Morarji Desai National Institute of Yoga, India), Teh Li Yin (Ministry of Health, Malaysia), Sivasangari Balan (Ministry of Health, Malaysia), Jiang Xu (Institute of Chinese Materia Medica, China Academy of Chinese Medical Sciences, China), Chris Lam Ka Yun (Chinese Medicine Regulatory Office, China).

WHO would like to extend its gratitude to the members of topic group on artificial intelligence and Traditional Medicine within the WHO-ITU FG-AI4H who contributed in the conceptualisation process of the document: Saketh Thrigulla (Ministry of Ayush, India), Bhavana Parashar (Institute of Genomics and Integrative Biology, India), Kenji Watanabe (Center for Kampo Medicine Keio University School of Medicine, Japan), Antonio Morandi (Ayurveda Point, Italy), Roberto Scavelli (Ayurveda Point, Italy), Cang Shik Yin (Kyung Hee University, Republic of Korea), Dong hyun Nam (Sangji University, Republic of Korea), Sumeet Goel (Ministry of Ayush, India), Kavita Garg (Ministry of Ayush, India).

The following WHO staff and consultants contributed to this document: Karthik Adapa (WHO Regional Office for South-East Asia), Marcelo d’Agostino (WHO Regional Office for the Americas), Myrna Marti (WHO Regional Office for the Americas), Keyrellous Adib (WHO Regional Office for Europe), Hani Farouk Abdel Hai (WHO Regional Office for Africa), Mohamed Dilip Hensman (WHO Regional Office for the Western Pacific), Arshad Altaf (WHO Regional Office for the Eastern Mediterranean), Han Eunkyung (WHO Regional Office for the Western Pacific), Rania K.t. Kawar (Department of Health Work Force [HWF]), Khassoum Diallo (HWF), Agya Mahat (HWF), Onyema Ajuebor (HWF), Tigest Tamrat (Sexual and Reproductive Health and Research), Joao Paulo Souza (WHO Regional Office for the Americas), Gonseth-Garcia Jonas (WHO Regional Office for the Americas), Philippe Christian Doo-Kingue (WHO Regional Office for Africa), Immaculee Mukankubito (WHO Regional Office for Africa), Adi Fawzi Al-Nuseirat (WHO Regional Office for the Eastern Mediterranean), Dorina Pirgari (WHO Regional Office for Europe), Geraldine Rosa Hill (WHO Regional Office for the Western Pacific), Madhur Gupta (WHO Regional Office for South-East Asia), Manisha Shridhar (WHO Regional Office for South-East Asia) and Denise Schalet (Former DHI).

WHO would like to express its special appreciation to the Ministry of Ayush, India, for their financial support in the development of this document.

Acronyms and abbreviations

AI	artificial intelligence
CDSS	clinical decision support systems
CoP	communities of practice
FG-AI4H	Focus Group on Artificial Intelligence for Health
FPIC	free, prior and informed consent
GI-AI4H	Global Initiative on Artificial Intelligence for Health
GTMC	WHO Global Traditional Medicine Centre
ICD-11	International Classification of Diseases, 11th revision
ICT	information and communication technology
IDSov	Indigenous Data Sovereignty
IP	intellectual property
ISO	International Organization for Standardization
ITU	International Telecommunication Union
LMICs	low- and middle-income countries
ML	machine learning
NLP	natural language processing
OCR	optical character recognition
PHC	primary health care
R&D	research and development
SDG(s)	Sustainable Development Goal(s)
TCM	Traditional Chinese Medicine
TG-TM	Topic Group AI for Traditional Medicine
TKM	Traditional Korean Medicine
TM	Traditional Medicine
UHC	universal health coverage
UN	United Nations
WIPO	World Intellectual Property Organization
WHO	World Health Organization

Background

The growing and transformative power of artificial intelligence (AI), including across the health sector, is increasingly valuable and relevant. To effectively harness this potential, the International Telecommunication Union (ITU), the World Health Organization (WHO), and the World Intellectual Property Organization (WIPO) have partnered on the Global Initiative on AI for Health (GI-AI4H), with a mission to enable, facilitate and implement AI solutions in health ecosystems through on the ground projects and programmes to deliver on the health-related SDGs (*1*).

Despite its rapid growth, the application of AI in Traditional Medicine (TM) remains mostly unexplored. Grey areas exist, requiring further research, evidence, data and debate. Understanding AI's potential, but also its risks and limitations, is crucial to safely approaching the integration of AI into TM.

The potential use of AI for health has also been acknowledged in international fora such as the G20's New Delhi Declaration (*2*), which strongly supported the harnessing of AI. The Gujarat Declaration (*3*), a multistakeholder agenda adopted at the first WHO Traditional Medicine Global Summit (*4*) in 2023, drives and supports the mandates at the WHO Global Traditional Medicine Centre (*5,6*), including responsible use of digital technologies such as AI in the domain of TM. Similarly, the Seventy Seventh World Health Assembly hosted a policy roundtable on AI for health which brought together Member States, intergovernmental organizations, research institutions and industries, and discussed opportunities, risks and governance relating to AI for health (*7*).

Purpose and approach

This technical brief offers insight into the rapidly evolving AI for health landscape and how it might be utilized in TM. Country, regional and global examples are presented to show how AI is currently being used in TM to support evidence-informed decision-making and policy-making to improve health systems and universal health coverage (UHC). The benefits that incorporating AI in TM can realize through knowledge sharing, informing multistakeholder research, and programmatic and policy discussions are highlighted, as are associated risks and challenges. This discussion is set in the context of regulatory and ethical considerations and concludes by identifying potential actions that could support effective and responsible integration of AI into TM.

Methodology

The document was developed by leveraging the findings of a literature review and supplementing this with knowledge and inputs captured during the conceptualization process with experts from the Topic Group on AI and Traditional Medicine (TG-TM) under the ITU-WHO Focus Group on Artificial Intelligence for Health (FG-AI4H) (*8*).

Literature review and search strategy

A literature review was conducted to map the latest findings, studies and publications with empirical knowledge pertinent to AI and Traditional Medicine (TM). The search strategy was iteratively refined in parallel with the literature search process, facilitating continuous adaptation based on emerging findings and their relevance to the research objectives.

The literature review search strategy focused on the following topics related to TM and digital technologies or AI: AI in health care and its relevance to TM; global perspectives on the application of information and communication technology (ICT)/AI in TM; AI for personality assessment in TM; electronic health records and standards, and their application in TM; AI in TM-specific supply chain management; digitalization of traditional knowledge, such as Indigenous Medical Systems; perspectives on reusable knowledge bases for TM; ICT/AI in drug discovery for TM; AI in TM diagnostics; ethical considerations related to Indigenous Knowledge; intellectual property (IP) considerations; AI and digitalization policy agendas at regional and Member State levels; general AI approaches to risk identification and management; the AI lifecycle; and TM-terminologies, Morbidity Codes, and other standards in Traditional Medicine.

Publications were included in the literature review if 1) the publication title and/or abstract mentioned the key terms listed above; 2) the publication was published in a peer-reviewed journal or by a governmental or UN body; 3) the publication was accessible through an open-access source; and 4) the publication was available in English.

The searches were conducted in two rounds using the bibliographic databases PubMed and Scopus and supplemented with publicly available search engines Google Scholar and Google Search. ScienceDirect, SpringerLink, Wiley Online Library, and Taylor & Francis Online were also searched. The first round yielded 89 sources, including peer-reviewed journal articles and grey literature published by governmental or UN agencies. Grey literature sources searched were the World Health Organization Institutional Repository for Information Sharing and the United Nations Digital Library. Following expert feedback and consultation, the second round collected additional use cases and expanded the search to include sources on policy and regulatory considerations. The second round yielded 66 sources. The study selection and data collection phases were conducted consecutively.

Expert consultations and review

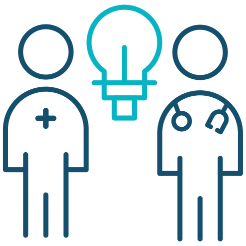
In September 2024, 60 participants from 15 countries across all six WHO regions participated in a hybrid consultation to exchange experiences and enhance understanding of how AI can advance Traditional Medicine. The experts each filled out a declaration of interest form that was reviewed by the WHO Secretariat and were determined not to have any conflicts of interest with the objectives of this brief.

The consultation was conducted online, in person and via email. The experts were members of ITU, WHO, WIPO and other UN agencies, governments, academic institutions and non-governmental organizations. The feedback collected was synthesized and structured into themes, which were then used to inform the research. Following the consultation, the experts were invited to give iterative feedback on the progress and development of this document.

Intended users

Policy-makers and government

Ministries of Health or TM, and other policy-makers will gain comprehensive insights into the role of AI in TM. This technical brief supports the education of policy-makers by providing an overview of guidance, regulatory frameworks and policies for consideration, helping them to craft policy-making from a point of understanding and awareness of AI, its potential and risks to TM.



Health systems and technical experts

Programme and technical specialists, including WHO experts and the scientific and medical community, as well as TM specialists and practitioners, will gain insights as the document broadens understanding of the potential of AI, as well as of associated risks and challenges, and equips experts with the knowledge necessary for navigating the concepts and evidence regarding the integration of AI and TM.

Digital technology experts

Developers, programmers and tech workers will gain valuable guidance on key areas of opportunity for advancing AI in TM. Emphasizing concepts of regulation, ethics and collaboration, this brief also highlights considerations for responsibly leveraging AI to enhance TM practices.

TM practitioners and users

TM practitioners, Indigenous Peoples, as well as local communities and overall TM user groups will gain accessible information to help them understand both the opportunities and the risks and challenges of AI to TM. This document showcases examples directly from Indigenous Peoples, as well as local communities and TM patients and highlights areas where the active participation of these communities and patients is needed to address risks related to data and knowledge, critical for advancing AI into TM.

Traditional Medicine in context

TM, encompassing Traditional Medicine and complementary medicine (*9*), stands as a crucial pillar in achieving UHC, given its widespread and sustained utilization by billions of people worldwide (*10*). For many people, TM is a primary approach, and the first treatment option within reach, in promoting health and well-being for all, aligning with the goals outlined in Sustainable Development Goal 3 (SDG) (*11*). Furthermore, its value extends beyond health (*12*): for example, it supports multiple dimensions of well-being, such as biodiversity and natural resource management, food security, livelihoods, nutrition, biocultural diversity and more (*13,14*), which approximates to the notion of integrative health (*15*).

The prevalence of TM is particularly notable in low- and middle-income countries (LMICs), with WHO reporting its use in 88% of its Member States (170 of 194) (*15*). The global popularity of TM is on the rise, driven by a growing interest in holistic health approaches that emphasize prevention, promotion and rehabilitation. Consequently, many countries are shifting their health care frameworks from simply medical care to the provision of comprehensive health care, slowly integrating TM into modern health systems and moving closer to the concept of UHC (*16–18*).

In addition, despite the general lack of publicly available evidence on the economic importance of TM at a global scale, some market researchers suggest that the value of the TM market[1] will reach US$ 583 billion by 2025 (*19*) and grow at 10–20% per year (*20*). Notably, the contributions of TM to local economies in both high-income countries and LMICs are highlighted by various resources. For instance, Australia's herbal medicine industry is valued at US$ 3.97 billion, while the Traditional Chinese Medicine (TCM) market stands at US$ 122.4 billion (*21*) and the Indian Ayush market at US$ 43.4 billion (*22*).

[1] Under the current WHO definition, there are differences between what constitutes a TM market and what TM is. The references showcased in this paragraph are studies focusing on economic and market-driven purposes and consider that the TM market spans different holistic, Indigenous and ancient therapies and products, such as Ayurveda, TCM, chiropractic, etc.

How is AI currently being utilized in Traditional Medicine?

This section discusses how AI and other frontier technologies are already being used and applied across different areas of health and TM, with examples from country, regional and global projects. Also highlighted are key areas, such as digitalization, data ownership and IP, that can accelerate the integration of AI into TM.

In health care

- **Diagnosis and prediction-based diagnosis.** Cutting-edge computer systems, enhanced with AI and other frontier technologies like machine learning (ML) and big data analysis, have the potential to advance personalized medicine by analysing individual health data such as medical records and imaging results and employing predictive analysis, potentially revolutionizing holistic health care (*23*). ML algorithms play a pivotal role in disease diagnosis and prognosis, potentially leading to the application of technology in TM-based personalized health care, which focuses on temperamental analysis or body type assessment. These algorithms can refine decision support systems based on TM parameters, optimizing their performance through the creation of a patient–physician interface leveraging natural language processing (NLP). Traditional methods such as pulse diagnosis, tongue examination, urine analysis, speech patterns and touch, as well as energetic assessments in acupuncture and Prakriti (body constitution) assessment in Ayurveda, can also benefit from AI algorithms and deep convolutional neural networks, aiding objective diagnosis and treatment monitoring. Health systems and technical experts in India, for instance, are developing ML algorithms to blend the latest knowledge of genomics with Ayurvedic principles with the aim of identifying predictive disease markers that can be used to inform recommendations for personalized preventive approaches (*24*).

Initiators: Health systems and technical experts

Ayurgenomics, India

This project represents an exciting intersection of Ayurveda and genomics, aiming to understand the genetic basis of Ayurvedic principles and practices. By integrating genomic data with Ayurvedic principles, the Ayurgenomics project seeks to identify predictive markers for diseases, enabling targeted prevention through personalized health recommendations. Machine learning algorithms are being developed to analyse Ayurvedic constitution types. Additionally, the Ayurgenomics framework is being applied to decipher the genomic and molecular basis of herbal formulations, enabling their repurposing for modern disease conditions (*24*).

In clinical care

- **AI-based clinical decision support systems** (CDSS) can help personalize TM interventions. In TM, CDSS could be used to recommend suitable treatment plans by analysing previously gathered information on symptoms, genetic or unique characteristics, and health histories of patients. Additionally, NLP-driven CDSS could help provide relevant treatment recommendations from classical TM texts, offering an opportunity to determine whether a patient's symptoms or condition would be better managed through Traditional, Complementary and Integrative Medicine or biomedicine (*25*). One such programme supporting the use of AI in these areas is Bridge2AI (*26*) in the United States of America, which is also seeking to boost research capability in the complementary and integrative health arena.

Initiators: Policy-makers and government, health systems and technical experts

Bridge2AI, United States

The Bridge2AI programme supports projects using AI for data analysis, personalization, predictive modelling, and integration of traditional and modern health approaches. The programme is collaboratively managed within the National Institute of Health, including the National Center for Complementary and Integrative Health (*27*).

- **AI-powered trial design.** AI can optimize the design of clinical trials for TM treatments by identifying the most relevant patient groups, appropriate dosages and key outcome measures. This is especially useful in areas where there is little research, as AI can suggest trial parameters based on similar treatments or medical fields.

In health research and drug development

- **Application of AI for drug development and health research.** There is immense potential for using emerging technologies such as AI in the field of drug discovery and related research (*28,29*). AI can be utilized for the identification of herbs, mapping of species, standardization of raw materials and finished formulations, and the analysis of probable herb-herb and herb-drug interactions to guide polypharmacy and integrative health care approaches. Moreover, the use of AI can support the development of precision medicine based on TM principles for personalized differential diagnosis and treatment approaches. In-silico models can be employed for lead optimization, dosage standardization and individualization, validation of reverse pharmacology models, and cataloguing and harmonizing various forms of TM used globally to prescribe the most promising interventions to patients. These applications can be categorized as follows.

- **Pattern recognition for drug development.** By unveiling patterns of drug usage within the extensive literature on diverse TM across the globe, systems can support novel drug development and formulation comprehension. This entails employing techniques such as frequency analysis, correlation analysis, complex network analysis and cluster analysis (*30*).
- **Genetic information analysis** to explore genetic data of medicinal plants and unveil shared properties among species/genera with similar TM parameters (for example, traditional Chinese, Korean or Japanese medicine, Rasa, Guna, Virya in Ayurveda and more).

Initiators: Policy-makers and government, health systems and technical experts

The Rooibos genomics programme, South Africa

This programme is focused on advancing medicinal plant genome analysis by generating a high-quality assembly of the rooibos genome, identifying genes linked to medicinal compounds and stress tolerance, and developing machine learning tools for genome mining. In collaboration with the South African National Bioinformatics Institute, which provides bioinformatics training and supports data analysis, the programme made significant strides in 2023. Its achievements include publishing a method for sequencing and assembling the 1.25Gbp rooibos genome, optimizing transcriptome analysis and sequencing 12 rooibos transcriptomes. The team also established a genome browser for visualization, collected samples from 105 rooibos ecotypes for comparative studies and conducted phenolic compound analysis. Additionally, they initiated a greenhouse experiment on drought stress and developed a neural network model to predict novel plant protein functions (*31*).

- **Identification and direct utilization of TM plants.** This leverages a reverse pharmacology approach by analysing big data from medical records to derive evidence-based insights on drug usage and intervention outcomes. Large data sets can also be interrogated to assist in the identification of medicinal plants. An AI-driven electronic tongue (e-tongue) can aid plant standardization by providing objective (*32*), reproducible sensory analysis that evaluates taste profiles and quality attributes of herbal and plant-based products (*33*). In Ghana, research has explored the use of Log Gabor filters, which mimic the human eye's visual cortex, to extract information about leaf texture from international plant data sets to support the development of a deep learning model that can identify and classify medicinal plants (*34*). Computer vision and augmented or virtual reality can also be used to understand the features of medicinal plants at botanical gardens and biodiversity parks.

Initiators: Health systems and technical experts, digital technology experts

Real-time identification of flora and fauna using ML techniques, India

The ability to automatically identify medicinal plants for TM use by images of their leaves would reduce the need for expert input and save time. However, differentiating leaves from their background in images is a complex task given variable lighting conditions in the environment. This study proposes a system for identifying plant species based on images of leaf samples using an improved vegetation index, ExG-ExR, which can extract more vegetative information from images than existing methods without requiring user-selected thresholds. The ExG-ExR index effectively identifies binary plant regions regardless of lighting. The original colour pixels of the binary image serve as a mask to isolate leaves as sub-images. Plant species are then classified by colour and texture features of each extracted leaf using a logistic regression classifier, achieving 93.3% accuracy (*35*,*36*).

Initiators: Health systems and technical experts

Textural analysis for medicinal plants identification, Ghana

Texture is key in computer vision, especially for identifying medicinal plants. Log Gabor filters, designed to mimic the human eye's visual cortex, outperformed traditional Gabor filters in extracting leaf textural features across multiple data sets, including those from the Centre of Plant Medicine Research in Ghana. Tested on nine classifiers, the Log Gabor filter achieved top accuracy rates (79%, 97% and 98%) significantly surpassing Gabor filters. These results suggest that combining Log Gabor features with deep learning could greatly enhance plant classification by capturing both simple and complex image features (*34*).

Initiators: Health systems and technical experts

Ethnobotany and AI for validating the potential bioactivity of medicinal plants, Democratic Republic of the Congo

This study investigated medicinal plants for influenza treatment, validating traditional uses through molecular modelling. Participants from IBI-Village identified 40 plants traditionally used for influenza care, including *Cymbopogon citratus* and *Ocimum gratissimum*. Molecular docking categorized plant compounds into five classes, showing stable complexes and specific hydrogen bonds with receptor sites. Molecular dynamics simulations highlighted key amino acid interactions, particularly with eugenol. The integration of molecular dynamics, docking and ethnobotany demonstrated the potential efficacy of *C. citratus* and *O. gratissimum* against influenza, suggesting that pharmaceuticals based on these plants' essential oils could enhance influenza management (*37*).

In health system management and planning

- **Utilizing hospital management information systems** to process patient records from TM health care facilities provides valuable data for analysis. This approach examines patient concepts based on TM principles and uncovers disease patterns and correlations. Combining AI-enabled electronic health records with handwriting recognition and optical character recognition (OCR) technologies, supported by the use of standardized terminologies (*38*), enhances data collection and accuracy, increasing data entry speeds and generating large amounts of analysable data. Innovations like MATLAB's ML handwriting recognition and Google's Cloud Vision application programming interface for OCR exemplify advancements in this field.

Preserving and advancing Traditional Medicine knowledge

- **Online repositories for TM knowledge** allow people to obtain scientific, technical and educational content on TM. One such example is the Virtual Health Library on Traditional Complementary and Integrative Medicine in the Americas Region (*39*). AI has been utilized in the backend of this Virtual Health Library to speed up cataloguing and facilitating the identification of relevant terms (*40*). The Ayurvedic historical imprints serve as a rich repository of traditional wisdom, documenting centuries-old practices (*41*), while the Traditional Knowledge Digital Library (TKDL) has digitized Traditional Medicine practices from Ayurveda, Siddha, Sowa Rigpa, and Yoga into a multilingual database that helps preserve indigenous knowledge (*42*).

Initiators: Policy-makers and government

Virtual Health Library on Traditional Complementary and Integrative Medicine in the Americas Region, Brazil

This library, developed and managed by the Latin American and Caribbean Center on Health Sciences Information of the Pan American Health Organization/WHO, has been promoting the presence, access, use and publication of scientific, technical and educational content relating to TM and Indigenous Knowledges of health care in the Americas Region through the collaboration of stakeholders. This initiative follows the support of the Brazilian Ministry of Health to create a knowledge platform and library for Brazilian TM (*39*).

- **Defensive protection against biopiracy.** The creation of comprehensive repositories of traditional knowledge, genetic resources and associated traditional practices can reduce the risk of unauthorized exploitation.

- **Conservation and identification of biodiversity.** Remote sensing technologies and ML algorithms can analyse satellite imagery to detect changes in vegetation cover and habitat loss, providing valuable insights for conservation planning and management.

- **NLP and automated literature reviews.** The NLP capabilities of AI can review and analyse vast amounts of existing literature, including medical research, historical TM records and anecdotal evidence, to highlight areas where research is lacking. AI can summarize trends and suggest potential research directions where traditional knowledge intersects with modern scientific gaps.

- **Translating Indigenous Knowledges.** AI can help translate and digitize oral traditions and lesser-known TM practices from Indigenous Peoples, as well as local communities, which may not be well documented. This process can bring hidden knowledge into mainstream research, potentially filling gaps where no formal evidence exists.

In policy-making for Traditional Medicine

- **Data governance models.** With some support from national authorities, Indigenous Peoples, as well as local communities across diverse settings, including in New Zealand, Canada, the United States and South America, are implementing customized data governance models that address several concerns regarding data privacy, storage, processing, use and identification (*43–49*). Unlike engines found in mainstream cloud service providers, these models address privacy at a more customized and granular level of access and permissions. The CARE and FAIR principles[2] for indigenous data governance were paramount in promoting principles for

[2] CARE: Collective benefit, Authority to control, Responsibility and Ethics. FAIR: Findable, Accessible, Interoperable, Reusable.

scientifically sound data management and stewardship in Indigenous Peoples, as well as local communities. This type of engagement has the potential to control personal and community data in a way that goes beyond data lifecycle management. Some models also encompass the design process and post-market surveillance of the corresponding data strategies, which are critical for any kind of technology development such as AI.

Originators: Policy-makers and government, TM practitioners and users

Māori Data Governance Model, New Zealand

In Aotearoa, the Māori Data Governance Model was developed to guide public service agencies in their management of Māori data, emphasizing self-determination and community needs (*43,44*). Under the model, the iwi-Māori work together with STATS New Zealand to realize the potential of data to make a sustainable, positive difference to outcomes for iwi, hapū and whānau. Implementation of the model is currently limited because of the lack of enabling Indigenous Data Sovereignty legislation. Similar efforts are seen in the Code of Ethics for Aboriginal and Torres Strait Islander Research from the Australian Government (*45*).

Originators: TM practitioners and users, digital technology experts

Terrastories, United States, Brazil, Colombia, Guyana

Developed by Digital Democracy, Terrastories is an application and a methodology created by the Amazon Conservation Team to map, record and safeguard place-based oral histories of lifestyle, cultural practices and healing practices, among others, from Indigenous Communities in the countries where the programme applies. Most maps and oral stories are only viewable by members of the community and accredited external users who have logged into the app using their community's credentials (*46*).

Originators: Policy-makers and government, TM practitioners and users

Our Data Indigenous, Canada

The project is a data collection app for social information, land surveys, environmental monitoring and more in First Nations communities in Manitoba, Canada. It is built considering principles of data and research sovereignty and in a way that respects and acknowledges the traditional knowledge and values of Indigenous Peoples, as well as local communities. Each community has control over their own data (*47*).

- **Agreements between national entities and Indigenous Peoples, as well as local communities for data advancement.** Although uncommon in the field of technology, such agreements have a larger impact on specific groups and populations, whether Indigenous or not. They are, however, useful to protect specific cultural and heritage aspects representative of such groups. Patient engagement and education is key to encourage patients to take an active interest in their data and, therefore, their health. Moreover, ethical documentation practices must be prioritized under such agreements to ensure prior informed consent and an equitable access and benefit-sharing ecosystem, safeguarding the interests of Indigenous Peoples, as well as local communities, and preventing biopiracy. A patent landscape study conducted by WIPO found that 10% of the patents filed for COVID-19 therapeutics accounted for 523 applications, related to traditional medicines – referring to preparations produced according to TM practices. Notably, China accounted for over 60% of these applications, with India and the Republic of Korea following (*50*).

Originators: Policy-makers and government, TM practitioners and users

Yoorrook, Australia

The Yoorrook Justice Commission is the first formal truth-telling process established as part of an agreement between the First Peoples' Assembly of Victoria and the Victorian Government. Based on specific data protection and sovereignty laws it considers a vast range of knowledge and experiences on matters such as land rights, history and sociocultural practices, among others. It can make recommendations for systems change and practical changes to laws, policy and practices in several areas, access to health care being one of them (*48,49*).

Areas of interest where limited or no evidence was found

- **Docking/simulation studies.** Utilizing high performance computing for docking/simulation studies can decipher drug action mechanisms and facilitate computationally aided new drug development from traditional medical knowledge, expediting drug development for emerging diseases. AI can enhance molecular docking by adopting a multicomponent approach to study polyherbal formulations, leveraging extensive databases of chemical constituents and simulation engines to model complex interactions – beyond the isolated network pharmacology typical in contemporary medicine – thus revolutionizing research and development (R&D) in TM through a deeper understanding of these formulations at the molecular level. For example, INPUT 2.0, an intelligent network pharmacology platform specific to TCM, automates an algorithm for performing network pharmacology of herbs and constructs networks connecting the molecule of interest and its targets (*51*).

- **Pathway identification.** ML algorithms can be employed to identify drug action pathways, something that is particularly relevant in TM with drugs containing multiple active compounds that act through diverse body pathways. For example, pathway identification can be used to understand the mechanism of action of polyherbal and herbomineral combinations used in Ayurveda.

- **Artificial chemical sensors** can be used to assess parameters like taste and smell across compounds, facilitating comparative analysis to identify key TM parameters (for example, Rasa, Guna, Virya and other systems parameters). The use of an electronic tongue and nose has effectively identified five basic tastes based on their chemical markers (*52*). Artificial chemical sensors can be further applied to understand the dynamics of Dosha, Dhatu, Mala and Prakriti in relation to the neuroendocrinological basis of fundamental principles of Ayurveda.

- **Comparative studies** on the usage of the same drug across diverse systems of medicine, such as Ayurveda, Unani, Sowa Rigpa, Homeopathy, TCM, Kampo, Koryo and others, can discern patterns and glean insights into therapeutic efficacy and applications.

- **Data augmentation.** AI can create synthetic data or augment limited datasets from TM practices to allow preliminary testing or hypothesis generation in areas where empirical data are scarce.

- **Cross-disciplinary learning.** AI can apply techniques from other fields of medicine or science to fill gaps in TM research. For instance, AI can analyse pharmacological data, molecular biology or modern medical treatments to suggest how TM practices may work in areas where there is little existing research.

- **Crowdsourcing.** AI can facilitate platforms where TM practitioners, researchers and patients contribute anecdotal data or personal experiences with treatments in areas lacking formal research. AI can then analyse these data to suggest trends and potential risks or benefits.

- **AI collaboration platforms.** AI can power research platforms that aggregate data from various sources – clinical studies, patient feedback, practitioner reports and historical data – to create a consolidated view of TM practices. This enables researchers to identify and investigate gaps in evidence.

General regulatory landscape

The WHO Global Report on Traditional and Complementary Medicine 2019[3] highlights a high level of adaptation of regulatory and policy measures among Member States (*15*). However, it also underscores the need for more technical guidance on research and evaluation, sharing information on regulatory issues and providing research databases.

While the report showcases some exemplary evidence, there is a gap between TM and biomedicine in specific legislation addressing the integration of digitalization or frontier technologies such as AI. Recently, there has been rapid progress in AI regulation, particularly in health care, at the Member State level. However, these regulations often overlook TM (*53*). For example, health regulations, despite covering critical areas like R&D, biotechnology and AI-enhanced technology development, tend to fail to address TM. This risks TM falling behind when updating regulatory frameworks and strategies to accommodate technological advancements. Despite these fragmented scenarios, the application of AI is being explored by TM researchers in various fields, which has the potential to inform regulation and policy-making (*54*).

Early-stage legislation on AI and AI in health presents a unique opportunity to explore synergies with TM, paving the way for stronger, context-specific regulatory frameworks. However, the role and significance of AI in TM has not yet been explored in a comprehensive or systematic way, making it difficult at this point in time to identify and establish connections between national AI policies, specific national AI regulations, national AI policy-making, and health regulations and TM. Table 1 provides an overview of the different current regulatory landscapes surrounding TM, AI and AI in health across various WHO regions and Member States.

Table 1 Regulatory landscape governing TM, AI and AI in health in WHO regions and Member States

WHO region	Number of Member States	National policy on TM (2018)[4] (*15*)	AI regulations or initiatives (any) (*55*)	Related AI policy initiatives in health (*56*)
African Region	47	41 (87%)	8 (17%)	3 (6%)
Region of the Americas	35	11 (31%)	10 (29%)	9 (26%)
South-East Asia Region	11	9 (82%)	4 (36%)	3 (27%)
European Region	53	11 (21%)	42 (79%)	19 (36%)
Eastern Mediterranean Region	21	9 (43%)	6 (29%)	1 (5%)
Western Pacific Region	27	15 (56%)	7 (26%)	4 (15%)
Global	194	96 (53%)	77 (36%)	39 (19%)

The numbers show how many Member States fall into each category, while the percentages show the proportion of Member States in each category compared with the total number of Member States in each WHO region.
Source: WHO TM Survey, Organisation for Economic Co-operation and Development AI index

[3] An updated report is due to be published in 2024.
[4] At the time this document was written, there was an ongoing update of the WHO TM Survey to be released in 2024, so the values and facts reported in Table 1 may vary.

Regulatory landscape for Indigenous Peoples, as well as local communities

In the context of TM, the adoption of frontier technologies can draw significant inspiration and guidance from the principles of Indigenous Data Sovereignty (IDSov) when engaging Indigenous Peoples, as well as local communities in the management of their health data (*57*). Spearheaded by Indigenous Scholars, Innovators and Knowledge-keepers, various countries and regions, including the United States, Canada, New Zealand, Australia, the Pacific and Scandinavia, are advocating for Indigenous Peoples' and local communities' rights over data relating to their membership, knowledge systems, customs or territories, challenging the notion that national governments hold sole authority over data, including health data (*58*).

Central to IDSov is the concept of collective stewardship, reflecting Indigenous Traditions of gathering and transmitting knowledge across generations (*59*). Indigenous Peoples, as well as local communities have long practised data gathering rooted in cultural protocols that govern data usage and sharing (*60*). IDSov principles emphasize collective consent, echoing the principles of free, prior and informed consent (FPIC) that are critical for health care decision-making processes, and mirror the ethical considerations behind digitalization and AI technologies (*61*). Similarly, these approaches mirror the conclusions in WHO's *Regulatory Considerations on Artificial Intelligence for Health* (*62*)[5] and *Ethics and Governance of Artificial Intelligence for Health* (*63*)[6]. Unfortunately, such interplay has not yet been tailored to the specifics of TM.

Despite progress, concrete regulatory mechanisms enabling Indigenous Peoples, as well as local communities to control and benefit from their data remain limited and challenges persist in fully implementing community data models without supportive legislation at the national level (*64*). A remarkable example is Canada's support for the First Nations Data Governance Strategy (*65*), which envisages a national network of information governance centres, including for health data governance (*66*), supported by legislation like the UN Declaration on the Rights of Indigenous Peoples.

National initiatives on digital health and Traditional Medicine

Leading TM countries such as Brazil, China, India, Japan and the Republic of Korea are making commendable efforts to expand the use of digital technologies in health care. However, it is important to note that digital health agendas and frontier technologies, including AI, still have limitations in addressing their interaction with TM specifically (*25*). For example, there are no TM-focused agendas in telehealth or primary care, in contrast to the trends observed in biomedicine.

[5] The document was also published as part of the ITU-WHO FG-AI4H deliverables. (FG-AI4H DEL02, Overview of regulatory concepts on artificial intelligence for health. [https://www.itu.int/pub/T-FG-AI4H-2022-3, accessed 2 November 2024]).
[6] The document was also published as part of the ITU-WHO FG-AI4H deliverables. (FG-AI4H DEL01, Ethics and governance of artificial intelligence for health. [https://www.itu.int/pub/T-FG-AI4H-2022, accessed 2 November 2024]).

Initiators: Health systems and technical experts

Context-Oriented Directed Associations (CODA), Republic of Korea

The Bio-Synergy Research Project of the Republic of Korea has developed a computer language to represent complex biological interactions to support construction of a network of potential interactions between chemicals, proteins and genes within, and between, organs and evaluate the therapeutic potential of chemical compounds found in traditional medicines from four Asian plants to treat blood disorders (*30*).

- **Brazil** has initiated efforts to incorporate digital technologies into TM practices, particularly within Indigenous Peoples, as well as local communities. The government has supported projects to develop digital health solutions that combine traditional Indigenous Knowledges with modern technologies to improve health care delivery and access in remote areas (*67,68*).

- **China** has been at the forefront of integrating digital technologies into TM. The Chinese government released the 14th Five-Year Plan under which TCM will be strengthened and further enhanced with information technologies and the TCM industry will be supported to transform and upgrade through digitalization (*69,70*).

- **India** has also taken steps to incorporate digital technologies into TM systems such as Ayurveda, Yoga, Naturopathy, Unani, Siddha, Sowa Rigpa and Homeopathy. The government has launched digital platforms and initiatives to provide online consultations, promote digital literacy among practitioners and facilitate the integration of TM with modern health care systems (*71,72*).

- **Japan** has been exploring the use of digital technologies in TM practices such as Kampo medicine. The government has supported research projects and initiatives aimed at integrating digital tools and platforms into Kampo practice, including the development of CDSS and electronic health records systems tailored to TM (*73,74*).

- **The Republic of Korea** has implemented policies to integrate digital technologies into traditional Korean medicine (TKM). The government has supported R&D in digital health technologies for TKM, including electronic health records systems, telemedicine platforms and mobile applications for patient care and education (*75*).

Initiators: Health systems and technical experts, digital technology experts

TCM Bank, China

The Sun Yat-sen University in China built the TCM Bank to provide standardized information about traditional Chinese medicines, ingredients, diseases and their corresponding gene targets. It establishes a comprehensive network with intelligent document identification and continuous (live) manual checks, and is for non-commercial purposes providing support for modern drug discovery (*33*).

Despite the presence of some consistent national agendas for digitalization and frontier technologies in health care, this report could not find publicly available evidence of holistic integration with TM. Critical areas for TM, such as R&D, IP and manufacturing, are often considered in isolation from TM.

Global frameworks for collaboration on AI and Traditional Medicine

At the Global Conference on Primary Health Care in Astana, Kazakhstan, in October 2018, the Declaration of Astana was adopted, renewing the commitments of the 1978 Alma-Ata Declaration. The declaration underscores the importance of primary health care (PHC) in achieving UHC and the SDGs. It emphasizes broadening access to high-quality, safe, effective and affordable health care services, including traditional medicines, vaccines, diagnostics and other technologies. It also highlights the importance of promoting accessibility, rational use and personal data protection. Advances in information systems are crucial for collecting high-quality, disaggregated data, improving disease surveillance and ensuring transparency and accountability in health system performance. Technologies aim to improve access to health care, service delivery, quality, patient safety and care coordination. Digital tools empower individuals and communities to identify health needs, participate in planning and service delivery, and maintain their health. The Astana Declaration also builds on the achievements of the Alma-Ata Declaration, addressing contemporary health challenges and reaffirming the global commitment to PHC as a fundamental strategy for better health outcomes for all (*76*).

The 2030 Agenda for Sustainable Development underscores the transformative power of ICT in advancing human progress and bridging the digital divide, fostering knowledge societies. There is a notable shift towards a citizen-centric health care approach, empowering individuals to actively participate in their health care journey through access to information and tools (*77,78*). Despite the increasing digitization and digitalization in health care, their full potential remains largely untapped in TM. To take these matters forward, WHO has been instrumental in promoting the standardization and development of benchmarking. For example, in 2019, WHO published a benchmark document for the training and practice of Ayurveda (*79*). Additionally, WHO has developed international standard terminologies for Ayurveda, Siddha, Unani and TCM, and has incorporated TM morbidity codes into the International Classification of Diseases, 11th revision (ICD-11), as TM Modules (*80,81*). These efforts facilitate the widespread adoption of TM terminologies and codes in electronic health records, enabling practical recording and reporting of health statistics related to TM.

Alongside TM standardization, in 2022, WHO and ITU introduced a working document calling for participation in a Topic Group AI for Traditional Medicine (TG-TM) under the work of the FG-AI4H (*82*). In 2013, TG-TM pre-published a topic description document exploring the concept of benchmarking AI for TM (*82*).

To further advance global collaborations on TM, WHO established the Global Traditional Medicine Centre (GTMC) with the support of the Government of India to harness the potential of various practices across the world through modern science and technology, including frontier technologies and AI (*4,5*). Thus far, the GTMC has a mandate to work on digital health and TM, which will further enhance the infusion of data and technology and the role of AI in future.

In line with this milestone, the first WHO Traditional Medicine Global Summit, held in India in 2023 (*4*), saw the emergence of work on TM by the GI-AI4H to advance the previous effort of the TG-TM (*8*) as part of the ITU-WHO FG-AI4H (*83*), which was concluded in the same year following its transition to the new GI-AI4H. The aim of the GI-AI4H in the realms of TM is to coordinate AI ecosystems to enable policy-making, facilitate resources and communities of practice, and implement AI in health at the frontline.

The World Intellectual Property Organization (WIPO) adopted the new Treaty on Intellectual Property, Genetic Resources and Associated Traditional Knowledge in 2024 (*84,85*). This treaty establishes a mandatory patent disclosure requirement – this requires patent applicants to disclose the country of origin of the genetic resources and/or the Indigenous Peoples, as well as local communities providing the associated traditional knowledge, if the claimed inventions are “based on” genetic resources and/or associated traditional knowledge. It also suggests the establishment of information systems (such as databases) of genetic resources and associated traditional knowledge, in consultation, where applicable, with Indigenous Peoples, as well as local communities and other stakeholders, taking into account their national circumstances.

Originators: Policy-makers and government, TM practitioners and users

WIPO Treaty on Intellectual Property, Genetic Resources and Associated Traditional Knowledge

The World Intellectual Property Organization (WIPO) Treaty on Intellectual Property, Genetic Resources and Associated Traditional Knowledge represents an international agreement to address the intersection of IP, genetic resources and traditional knowledge. It includes specific provisions for Indigenous Peoples, as well as local communities, ensuring their valuable knowledge and practices are recognized (*85*).

Furthermore, Member States' individual prerogatives to approach the International Organization for Standardization (ISO) for the formulation of TM standards as part of ISO/TC 215 – Health informatics standardization represent forward-looking steps towards integrating digital health technologies into TM, thus opening the door for more ambitious applications, including AI (*86–88*). Similar efforts, such as ISO/DTR 4421:2023 Health informatics – Introduction to Ayurveda informatics, ISO/TS 5044:2023 Health informatics – Information model for quality control of traditional Chinese medicinal products, ISO/TS 5118:2022 Health informatics – Categorial structure of representation for evaluation of clinical practice guidelines of TCM and ISO/TS 5346:2022 Health informatics – Categorial structure for representation of TCM clinical decision support system, are integral to enabling global standards for TM (*89,90*).

Risks and challenges in the application of AI in Traditional Medicine

General overarching considerations

WHO's guidance on *Ethics and Governance of Artificial Intelligence for Health* (*63*) identifies five major areas commonly associated with risks and challenges in the application of AI in health: 1) scientific and research domains; 2) the development of digital infrastructures; 3) targeting underrepresented and vulnerable population groups; 4) strategizing investment, procurement and public finance initiatives; and 5) addressing diversity, languages and cultural contexts. WHO's guidance on *Regulatory Considerations on AI for Health* (*62*) also addresses some of the risks, and approaches AI from a total product lifecycle and risk management perspective. It underscores intended use and analytical and clinical validation, data quality, privacy and data protection, and engagement and collaboration.

While most of these approaches may well be applicable to the application of AI in TM, the sectoral singularities necessitate a tailored and domain-specific approach as this is where the interaction with AI may result in potential harm to patients.

- **Biopiracy threat.** Biopiracy refers to the unauthorized appropriation of Indigenous Knowledges, biological resources or traditional cultural expressions, typically for commercial gain. In the context of TM, this threat arises through the potential exploitation of knowledge and resources without proper acknowledgement, consent or compensation to Indigenous Peoples, the communities and cultures from which the knowledge originates, leading to the loss of cultural autonomy and sovereignty. This threat could manifest in:
  - **Exploitation of TM knowledge,** encompassing its repositories on medicinal plants, herbal remedies, acupuncture and other therapeutic practices.
  - **Commercialization without consent,** when AI algorithms are used to develop and market pharmaceuticals or health supplements based on TM principles, but benefits do not flow back to Indigenous Peoples, communities, perpetuating inequalities and exploitation.
  - **Loss of cultural heritage,** thus undermining the economic rights of Indigenous Peoples as well as local communities and eroding their cultural heritage and identity by commodifying and commercializing products without respect for the cultural context from which they emerged.

Initiators: Policy-makers and government, health systems and technical experts

The Traditional Knowledge Digital Library (TKDL), India

India was the first country to launch a Traditional Knowledge Digital Library (TKDL) to document and protect Indian traditional medicinal knowledge from its ancient medical practices rooted in Ayurveda, Sidha and Unani. The TKDL is available in several languages and linked to patent search databases. It has extensively digitized text-based formulations of Ayurveda, Unani, Siddha, Sowa Rigpa and practices of Yoga, and has made the data available to leading patent offices with a multilingual option on a non-disclosure agreement basis to prevent biopiracy based on the prior art. These data are critical for research and development, and can also be useful for algorithm training and model shaping of AI. The digital library has set international specifications and standards for setting up traditional knowledge databases based on TKDL specifications (*42*).

- **Gaps in digital infrastructure and literacy** may hinder equitable access, adoption and effective utilization of digital technologies, including AI. Indigenous Peoples as well as local communities who practise TM are particularly vulnerable to limited access to technology as well as to essentials for digital infrastructure, such as reliable Internet connectivity or electricity. Digital literacy, on the other hand, refers to the ability to understand and use digital technologies effectively. This is essential for care recipients and health workers to leverage the use of digital technologies, including AI. They may face additional challenges related to language barriers or cultural differences when interacting with digital technologies as the user interfaces or educational materials may not be accessible or culturally appropriate, further exacerbating the digital divide.

- **Inadequate data infrastructure.** AI-enabled health technologies require large volumes of data, either medical or from patients, for training and validation. The absence of robust data and data infrastructure, such as electronic health records, standardized formats for data and its annotation, or databases documenting TM practices, hampers data utilization. Moreover, the lack of adequate and good-quality data for TM itself poses a huge risk as model training may lead to inaccurate statements.

- **Insufficient engagement with and recognition of TM.** Insufficient digital adaptation of AI systems to the cultural context of TM practices can lead to cultural insensitivity or misappropriation, potentially undermining trust and acceptance within these communities. Moreover, the detachment of AI technologies from TM can lead to the perception of reduced value and may result in the underutilization, underestimation and misconception of TM as a complementary practice to biomedicine. It may also lead to discrimination against communities and limited recognition and rights, reinforcing the algorithmic bias and misrepresentation of relevant TM populations.

- **Localization versus integration of AI solutions in TM.** The primary challenge in this area lies in balancing context-specific adaptability with global applicability. Localized AI solutions in different Member States may face issues of limited scalability, inconsistent quality, data privacy concerns and health care fragmentation. Conversely, integrated AI solutions risk lacking contextual relevance and cultural sensitivity, and face data diversity challenges, infrastructure disparities and regulatory compliance complexities. Hybrid approaches for integrating AI into TM that combine adaptable core frameworks, collaborative development, scalable structures, regulatory harmonization and continuous feedback mechanisms are essential.

Risk management throughout the AI lifecycle and beyond

To effectively navigate the adoption of AI in TM, it is crucial to understand and address the potential risks across the various stages of the AI lifecycle, as well as critical stages beyond it. This includes both the early stage of problem identification and post-market activities (*62*). Each phase presents a range of challenges and considerations to ensure the tailored and responsible integration of AI in TM.

Problem identification

- **Critically assess the appropriateness and necessity of AI technologies.** Before designing AI technologies, it is crucial to identify and assess the specific risks associated with a particular TM domain. This involves critically examining whether AI can genuinely address the identified problem and determining the nature of these problems. Are they context-specific, or do they apply broadly across different TM practices? Without thorough evaluation, there is a risk of developing siloed AI solutions that may not effectively solve the problem, leading to potential non-use, misapplication and ethical concerns.

- **Evaluate institutional readiness and workforce competences.** It is crucial to conduct thorough readiness assessments, even if a problem has already been identified. Embarking on the development, procurement or partnering of innovation and technological resources for developing AI technologies may not be feasible because of a lack of organizational and institutional capacities.

- **Review legal frameworks.** It is important to review the existing legal frameworks and guidelines, which apply to AI and TM.

Design

- **Prioritizing usability and human factors in AI applications for TM.** If usability and human factors principles are not explicitly considered and applied, AI solutions in TM risk being ineffective and difficult to use. This can lead to poor adoption, user frustration and decreased effectiveness of AI technologies, ultimately hindering the integration and benefits of AI in TM practices. Ensuring these principles are considered is crucial for creating user-friendly, efficient and supportive AI systems that meet the needs of practitioners and users.

- **Apply a participatory design approach.** Without the active involvement of end users, stakeholders and communities, the resulting technology may not meet their needs, preferences or cultural contexts. This can cause issues such as cultural irrelevance, resistance and mistrust from TM practitioners and Indigenous Peoples, as well as local communities. Additionally, without proper engagement, a limited understanding of TM can result in failure to capture essential TM knowledge. Lack of engagement may also lead to short-sighted designs that do not address the underlying needs or priorities of TM practitioners and patients, undermining the sustainability and impact of AI technologies.

- **Include ethical considerations and values.** By not considering the distinct ethical principles that guide TM practices, there is a high risk of overlooking or disregarding important approaches such as notions of privacy, FPIC and confidentiality among Indigenous Peoples, as well as local communities. This is particularly noticeable when utilizing digital tools for documenting evidence without considering linguistic variety or cultural specificity.

- **Be mindful of good-quality data.** In TM, especially in not-so-well-regulated or -standardized practices, obtaining good-quality data can be challenging because of factors such as variability in treatment approaches, reliance on qualitative or sensorial assessment and a lack of appropriate data collection methods. Without access to reliable and representative training data, AI models may not generalize well to real-world clinical scenarios, leading to poor performance and limited adoption. Moreover, a lack of good-quality data can reinforce biases and imbalances in training data, thus skewing AI algorithms and leading to inaccurate or unfair outcomes, reinforcing inequity and disparities in access to high-quality TM health care.

- **Develop targeted communications to interpret AI models.** In TM, treatment decisions are often based on nuanced clinical judgments, expert knowledge and holistic perspectives that may not be easily captured or represented in data. Without interpretability and explainability in AI models, practitioners may be hesitant to trust or rely on AI-generated recommendations, preferring instead to rely on their own expertise and intuition. Ensuring that AI models are interpretable and explainable is critical for fostering acceptance and adoption in TM settings.

Development

- **Create benchmarking frameworks.** This is the most relevant risk during the development phase as, without such frameworks, the use of AI in TM may lack the standardized metrics, criteria and benchmarks against which algorithms, models or systems can be evaluated and compared. This impacts directly on quality assurance and validation, which may lack objective criteria for assessing performance under the specifics of TM practices and contexts, increasing the risk of errors, biases or suboptimal outcomes. Moreover, without standardized benchmarks and protocols, developers may struggle to ensure seamless integration and interoperability, leading to fragmentation, inefficiencies and compatibility issues in AI deployment in TM contexts.

- **Ensure ethical and regulatory compliance.** Responsible AI modelling and evaluation often incorporates ethical guidelines, regulatory requirements and best practices. Without clear benchmarks for ethical and regulatory compliance, developers may inadvertently overlook important considerations such as privacy, security, transparency and fairness in their AI technologies for TM, increasing the risk of ethical violations or regulatory non-compliance. AI assistance can be incorporated successfully in ensuring ethical and safe practice of TM, compliant with modern standards.

- **Conduct comparative analysis to validate the performance of AI models.** Without benchmarking data and comparative analyses, developers may struggle to identify areas for improvement, optimize performance and iterate effectively. This hinders innovation and progress in TM-related AI R&D, directly impacting patient confidence in the safety, efficacy and validity of AI technologies. Ensuring there are frameworks that provide valuable insights into the strengths and weaknesses of AI algorithms is crucial for maintaining high standards in development.

- **Reduce disparities in AI training and testing data.** Given the nature of TM, significant disparities between the intended target population and the input or output distributions can be expected. Hence AI solutions may not be effective or equitable. It is essential to pre-identify and establish measures to address these disparities throughout the development cycle, ensuring that good-quality data flow for representativity and inclusiveness.

Deployment

- **Set up post-market surveillance mechanisms.** Post-market surveillance is essential for monitoring the safety, efficacy and real-world performance of AI technologies. Inadequate surveillance mechanisms may overlook interactions of traditional remedies or treatment in unforeseen ways, potentially leading to adverse effects or safety risks for patients. Additionally, AI technologies for TM may not deliver the expected therapeutic benefits or may fail to meet the needs of TM practitioners and patients, leading to suboptimal outcomes and dissatisfaction.

- **Engage end users for adverse event reporting.** The participation of TM patients and communities in the deployment and post-market surveillance of AI technologies may enhance timely communication and delivery of evidence regarding adverse events. A failure to articulate adequate deployment strategies that incorporate TM users, and Indigenous Peoples, as well as local communities may delay appropriate interventions and corrective actions to mitigate risks and improve patient safety. Reauthorization processes for AI technologies may also be compromised through a lack of information on non-compliance, quality control lapses or deviations from established standards.

Post-market and beyond

- **Monitor and anticipate adverse events.** Adverse events could cause serious issues in diverse and unique domains of TM. Without a plan for monitoring and anticipating adverse events, safety risks may not be properly identified or managed. Key considerations include a common understanding of the definition of an adverse event by different stakeholders, as well as ways to report and learn from adverse events. Contingency plans to phase out an AI system are needed should the AI cause inadequate monitoring of adverse events. Such contingency plans should encompass conducting safety investigations and ensuring that health system workflows can continue seamlessly.

Considerations for policy and practice

Regulatory frameworks and legislation

Adapt WHO guidance on frontier technologies to TM. Tailor existing WHO guidelines to the specific context of TM, ensuring that they capture and address the unique principles, practices and cultural considerations of TM.

Update TM survey to include digitalization and frontier technologies concepts. Approach WHO Member States to update evidence on the utilization of digitalization and frontier technologies that specifically apply to TM. This is critical to assess the current landscape and identify areas of opportunity and risk.

Co-create mechanisms to translate WHO guidance on frontier technologies into policy-making. WHO guidance is a relevant source for evidence-informed decision-making. Diverse mechanisms (for example, toolkits, workshops, courses) are required for translating recommendations into policy-making and to drive effective mainstreaming and implementation in the field.

Empowerment and capacity-building

Prepare education and training programmes targeting the integration of AI into TM. Develop formative training programmes, cross-training initiatives and digital literacy initiatives for AI developers, TM practitioners and policy-/decision-makers. Equip them with the skills needed to understand and apply AI in the context of TM, facilitating the translation of guidelines into actionable strategies.

Build and facilitate communities of practice (CoP) around TM and AI. Strategic CoP designed to bring WHO TM experts together with policy-makers and TM practitioners are critical to leveraging technical expertise and familiarizing members with the concepts and latest developments of frontier technologies, as well the opportunities and risks.

Build working groups targeting critical areas for integrating TM into AI such as IP, policy and legal design, ethics and regulation, and AI technologies' design and development. Multidisciplinary approaches beyond TM and frontier technologies are needed to advance AI into TM.

Targeting biopiracy and data governance

Tailor strategies to build robust data governance targeting Indigenous Peoples, as well as local communities. Approach Indigenous Peoples as well as local communities already engaged in data governance and sovereignty discussions to develop guidelines at the country level. Collaborate with statistics offices and Ministries of Health to ensure inclusive and transparent data governance practices based on good practices to protect Traditional Knowledges data.

Co-create and advance existing repositories on the applications of frontier technologies into TM. Collaborate with the GTMC to compile a comprehensive list of frontier technologies available across different TMs as a basis for mainstreaming these concepts with various TM users, and Indigenous Peoples, as well as local communities to foster awareness, innovation and advancement.

Cooperation and collaboration

Enhance global collaboration for harmonizing the TM lexicon and diverse data formats to AI. Bi- and multilateral collaboration is critical for the transfer of technology and expertise to harmonize the terminology and data formats of TM into AI. This work should facilitate data sharing, interoperability and standardization, in particular for R&D and patient treatment. The ITU standards-setting platform can be leveraged to develop international technical standards for interoperable data formats as well as data handling and assessment best practices.

Utilize the Global Traditional Medicine Library as a pivot for co-creating and facilitating collaborative environments. Knowledge-to-practice environments are critical for advancing and mainstreaming AI in TM by bringing Indigenous Peoples, as well as local communities and TM users together with experts, scientists and policy-makers and IP offices. A one-stop-shop centre of knowledge could be useful for strengthening networks and sharing knowledge.

Public awareness and equity and promotion of inclusion

Launch public awareness campaigns to educate the general public as well as key stakeholders in the domain of technology and TM about the potential benefits and risks of the application of AI in TM. Encourage active participation and feedback from TM patients, caregivers and community stakeholders in shaping health care policies and priorities.

Conclusion

AI is already playing a key and rapidly evolving role in health care and is beginning to be used in TM in innovative and exciting ways. This technical brief has sought to provide an insight into the current utilization and potential of AI in TM and to highlight knowledge gaps, risks and areas where action is required to safeguard the knowledge and practices of Indigenous Peoples, as well as local communities and the well-being of TM patients. Advancing the use of AI within TM, and equipping individuals with the knowledge they need to benefit from it, offers an opportunity to tap into the potential of TM to support the achievement of UHC. However, there is an associated need to develop holistic frameworks tailored to TM in areas such as regulation, knowledge sharing, capacity building, data governance and the promotion of equity, to ensure the safe, ethical and evidence-based integration of frontier technologies such as AI into the TM landscape and that the authenticity of the traditional knowledge and the fundamental principles of traditional medicines are not comprised during their translation into the language of AI.

References

1. Global Initiative on Artificial Intelligence for Health (GI-AI4H) (https://www.who.int/initiatives/global-initiative-on-ai-for-health, accessed 27 September 2024).
2. G20 New Delhi Leaders' Declaration. New Delhi, India, 9–10 September 2023 (https://www.mea.gov.in/Images/CPV/G20-New-Delhi-Leaders-Declaration.pdf, accessed 19 September 2024).
3. WHO Traditional Medicine Global Summit 2023 meeting report: Gujarat Declaration. Geneva: World Health Organization; 2023 (https://www.who.int/publications/m/item/who-traditional-medicine-summit-2023-meeting-report--gujarat-declaration, accessed 19 September 2024).
4. WHO Traditional Medicine Global Summit, 17–18 August 2023 (https://www.who.int/initiatives/who-global-traditional-medicine-centre/traditional-medicine-global-summit, accessed 15 October 2024).
5. WHO Global Traditional Medicine Centre. (https://www.who.int/initiatives/who-global-traditional-medicine-centre/our-work, accessed 13 March 2024).
6. Cabinet Approves Establishment of WHO Global Centre for Traditional Medicine in India (https://pib.gov.in/PressReleasePage.aspx?PRID=1804289, accessed 13 March 2024).
7. Artificial Intelligence for health: opportunities, risks, and governance. Geneva: World Health Organization (https://www.who.int/news-room/events/detail/2024/05/30/default-calendar/artificial-intelligence-for-health-opportunities-risks-and-governance, accessed 19 September 2024).
8. FG-AI4H Topic Group description: Traditional medicine (https://www.itu.int/en/ITU-T/focusgroups/ai4h/Documents/tg/CfP-TG-TM.pdf, accessed 30 August 2024).
9. Traditional, complementary and integrative medicine. World Health Organization (https://www.who.int/health-topics/traditional-complementary-and-integrative-medicine, accessed 13 March 2024).
10. To achieve health for all, embrace tradition, innovation and evidence. World Health Organization; 2022 (https://www.who.int/southeastasia/news/opinion-editorials/detail/to-achieve-health-for-all--embrace-tradition--innovation-and-evidence, accessed 13 March 2024).
11. SDG 3: Ensure healthy lives and promote well-being for all at all ages. United Nations Sustainable Development (blog) (https://www.un.org/sustainabledevelopment/health/, accessed 13 March 2024).
12. WHO convenes first high-level global summit on traditional medicine to explore evidence base, opportunities to accelerate health for all. World Health Organization; 2023 (https://www.who.int/news/item/10-08-2023-who-convenes-first-high-level-global-summit-on-traditional-medicine-to-explore-evidence-base--opportunities-to-accelerate-health-for-all, accessed 27 September 2024).
13. Linhares Y, Kaganski A, Agyare C, Kurnaz IA, Neergheen V, Kolodziejczyk B et al. Biodiversity: the overlooked source of human health. Trends Mol Med 2023;29;173–187 (https://doi.org/10.1016/j.molmed.2022.12.002).
14. Workshop on biodiversity, traditional knowledge, health and well-being. Pan American Health Organization/World Health Organization; 2023 (https://tcim-globalsummit.bvsalud.org/workshop-on-biodiversity-traditional-knowledge-health-and-well-being/, accessed 27 September 2024).
15. WHO Global Report on Traditional and Complementary Medicine 2019. World Health Organization; 2019 (https://iris.who.int/handle/10665/312342, accessed 27 September 2024).
16. Park YL, Canaway R. Integrating traditional and complementary medicine with national healthcare systems for universal health coverage in Asia and the Western Pacific. Health Syst Reform 2019;5(1):24–31 (https://doi.org/10.1080/23288604.2018.1539058).

17. WHO Universal Health Coverage (UHC). World Health Organization; 2023 (https://www.who.int/news-room/fact-sheets/detail/universal-health-coverage-(uhc), accessed 13 March 2024).
18. Kasilo OMJ, Wambebe C, Nikiema J-B, Nabyonga-Orem J. Towards universal health coverage: advancing the development and use of traditional medicines in Africa. BMJ Glob Health 2019;4(suppl 9):e001517 (https://doi.org/10.1136/bmjgh-2019-001517). 18
19. The Global Wellness Economy: Looking Beyond COVID. Global Wellness Institute; 2021 (https://globalwellnessinstitute.org/traditional-complementary-medicine-and-public-health-prevention-personalized-medicine-the-global-wellness-economy-looking-beyond-covid/, accessed 27 September 2024).
20. WTO agreements and public health: a joint study by the WHO and the WTO secretariat. World Health Organization and World Trade Organization: 2002 (https://www.wto.org/english/res_e/booksp_e/who_wto_e.pdf, accessed 13 January 2025).
21. Liang Z, Hu H, Li J, Yao D, Wang Y, Un COL. Advancing the regulation of traditional and complementary medicine products: a comparison of five regulatory systems on traditional medicines with a long history of use. Evid Based Complement Alternat Med 2021;2021:5833945 (https://doi.org/10.1155/2021/5833945).
22. Minister of State for New and Renewable Energy and Power, Shri Shripad Yesso Naik, Highlights Decadal Achievements of Ministry of Ayush (https://pib.gov.in/PressReleasePage.aspx?PRID=2079777#:~:text=Economic%20Impact,has%20further%20strengthened%20the%20sector, accessed 8 January 2025).
23. Ahsan MM, Luna SA, Siddique Z. Machine-learning-based disease diagnosis: a comprehensive review. Healthcare (Basel) 2022;10:541 (https://doi.org/10.3390/healthcare10030541).
24. Prasher B, Negi S, Aggarwal S, Mandal AK, Sethi TP, Deshmukh SR et al. Whole genome expression and biochemical correlates of extreme constitutional types defined in Ayurveda. J Transl Med 2008;6:48 (https://doi.org/10.1186/1479-5876-6-48).
25. Ng JY, Cramer H, Lee MS, Moher D. Traditional, complementary, and integrative medicine and artificial intelligence: novel opportunities in healthcare. Integ Med Res 2024;13:101024 (https://doi.org/10.1016/j.imr.2024.101024).
26. Bridge2AI (https://bridge2ai.org, accessed 27 September 2024).
27. NIH launches Bridge2AI program to expand the use of artificial intelligence in biomedical and behavioral research; 2022 (https://www.nccih.nih.gov/news/press-releases/nih-launches-bridge2ai-program-to-expand-the-use-of-artificial-intelligence-in-biomedical-and-behavioral-research, accessed 25 March 2025).
28. Khan SR, Al Rijjal D, Piro A, Wheeler MB. Integration of AI and traditional medicine in drug discovery. Drug Discov Today 2021;26:982–992 (https://doi.org/10.1016/j.drudis.2021.01.008).
29. Liu G, Xie Y, Sun Y, Zhang K, Ma J, Huang Y. Drug research and development opportunities in low- and middle-income countries: accelerating traditional medicine through systematic utilization and comprehensive synergy. Infect Dis Poverty 2022;11:27 (https://doi.org/10.1186/s40249-022-00954-4).
30. Yu H, Jung J, Yoon S, Kwon M, Bae S, Yim S et al. CODA: Integrating multi-level context-oriented directed associations for analysis of drug effects. Sci Rep 2017;7:7519 (https://doi.org/10.1038/s41598-017-07448-6).
31. South African National Bioinformatics Institute. Annual report 2023 (https://www.sanbi.ac.za/wp-content/uploads/2024/05/SANBI-AR-2023.pdf, accessed 27 September 2024).
32. Li X, Gao X, Liu R, Wang J, Wu Z, Zhang L, Li H, Gui X, Kang B, Shi J. Optimization and validation of the protocol used to analyze the taste of traditional Chinese medicines using an electronic tongue. Exp Ther Med 2016;12:2949–2957 (https://doi.org/10.3892/etm.2016.3733).

33. TCM Bank. Herbs (https://tcmbank.cn/Herbs, accessed 27 September 2024).
34. Twum F, Missah YM, Oppong SO, Ussiph N. Textural analysis for medicinal plants identification using log Gabor filters. IEEE Accesss 2022;10:83204–83220 (https://doi.org/10.1109/ACCESS.2022.3196788).
35. Sivaranjani C, Kalinathan L, Amutha R, Kathavarayan RS, Jegadish Kumar K. Real-time identification of medicinal plants using machine learning techniques. 2019 International Conference on Computational Intelligence in Data Science (ICCIDS), Chennai, India, 2019, pp 1-4 (https://doi.org/10.1109/ICCIDS.2019.8862126).
36. Bhelkar NS, Sharma A. Identification and classification of medicinal plants using leaf with deep convolutional neural networks. IJHS. 2022;6(S6):11596–605, https://www.neliti.com/publications/577630/identification-and-classification-of-medicinal-plants-using-leaf-with-deep-convo, accessed 1 October 2024).
37. Pisco MM, Georges GK, Monizi M, Colette MA, Pius TM, Virima M, Ngbolua K. Integrating ethnobotany and artificial intelligence to validate the potential bioactivity of two medicinal plants traditionally used in the treatment of influenza in IBI-Village and surrounding areas, Democratic Republic of the Congo. Nat Res Human Health 2024;4:230–246 (https://doi.org/10.53365/nrfhh/187385).
38. Srikanth N, Rana R, Singhal R, Jameela S, Singh R, Khanduri S, Tripathi A, et al. Mobile app-reported use of traditional medicine for maintenance of health in India during the COVID-19 pandemic: cross-sectional questionnaire study. JMIRx Med 2021;2(2):e25703 (https://doi.org/10.2196/25703).
39. Virtual Health Library on Traditional Complementary and Integrative Medicine (VHL TCIM) (https://mtci.bvsalud.org/en/about/, accessed 27 September 2024).
40. BIREME Bulletin nº 94; 18 January 2025 (https://boletin.bireme.org/en/2025/01/18/bireme-bwp-24-25-main-results/, accessed 25 March 2025).
41. Showcase of Ayurvedic Historical Imprints (SAHI). About SAHI (https://niimh.nic.in/sahi/about.php, accessed 3 February 2025).
42. Traditional Knowledge Digital Library Unit (TKDL). New Delhi: Council of Scientific & Industrial Research (https://www.csir.res.in/documents/tkdl, accessed 14 March 2024).
43. Maori Data Governance Model. Te Kahui Raraunga (https://www.kahuiraraunga.io/maoridatagovernance, accessed 13 March 2024).
44. Mana Ōrite Relationship Agreement (https://www.digital.govt.nz, accessed 13 March 2024).
45. AIATSIS Code of Ethics for Aboriginal and Torres Strait Islander Research. 2020 (https://aiatsis.gov.au/sites/default/files/2020-10/aiatsis-code-ethics.pdf, accessed 27 September 2024).
46. Terrastories (https://terrastories.app, accessed 27 September 2024).
47. Our Data Indigenous (https://ourdataindigenous.ca/, accessed 27 September 2024).
48. Yoorrook Justice Commission. About Yoorrook. (https://yoorrookjusticecommission.org.au/about/, accessed 27 September 2024).
49. Yoorrook Justice Commission. Indigenous data sovereignty and data governance. 2022 (https://yoorrookjusticecommission.org.au/wp-content/uploads/2022/04/041922_Yoorrook_DataSovereigntyGuidance.pdf, accessed 27 September 2024).
50. WIPO. Patent Landscape Report Covid-19 vaccines and therapeutics, Insights into related patenting activity throughout the pandemic; 2023 (https://www.wipo.int/edocs/pubdocs/en/wipo-pub-1075-23-en-covid-19-vaccines-and-therapeutics.pdf, accessed 20 January 2025).
51. Li X, Tang Q, Meng F, Du P, Chen W. INPUT: An intelligent network pharmacology platform unique for traditional Chinese medicine. Comput Struct Biotechnol J 2022;20:1345–51 (https://doi.org/10.1016/j.csbj.2022.03.006).

52. Lei K, Yuan M, Li S, Zhou Q, Li M, Zeng D, Guo Y, Guo L. Performance evaluation of E-nose and E-tongue combined with machine learning for qualitative and quantitative assessment of bear bile powder. Anal Bioanal Chem 2023;415:3503–3513 (https://doi.org/10.1007/s00216-023-04740-5).
53. AI Index Report 2023 – Artificial Intelligence Index (https://aiindex.stanford.edu/report/, accessed 13 March 2024).
54. Wu C, Chen J, Leung E, Chang H, Wang X. Editorial: Artificial intelligence in traditional medicine. Front Pharmacol 2022;13:933133 (https://doi.org/10.3389/fphar.2022.933133).
55. OECD.AI Policy Observatory. AI & Health (https://oecd.ai/en/site/health, accessed 8 October 2024).
56. OECD AI & Health Tracker (https://oecd.ai/en/dashboards/policy-areas/PA11)
57. Kukutai T. Indigenous data sovereignty—a new take on an old theme. Science 2023;382:eadl4664 (https://doi.org/10.1126/science.adl4664).
58. Caballar RD. How Indigenous groups are leading the way on data privacy. Scientific American June 7, 2023. (https://www.scientificamerican.com/article/how-indigenous-groups-are-leading-the-way-on-data-privacy/, accessed 13 March 2024).
59. Leonard K, Russo S, Martinez A, McElroy L, Garba I, Jennings L et al. CARE Statement for Indigenous Data Sovereignty. Retrieved from Office of the Secretary-General's Envoy on Technology website; 2023 (https://www.un.org/techenvoy/sites/www.un.org.techenvoy/files/GDC-submission_WAMPUM_Lab_and_the_Collaboratory_for_Indigenous.pdf, accessed 27 September 2024).
60. Nakashima D. Indigenous knowledge in global policies and practice for education, science and culture. UNESCO Digital Library; 2010 (https://unesdoc.unesco.org/ark:/48223/pf0000265855, accessed 13 March 2024).
61. Diviacchi T. Indigenous data sovereignty and open data. PLOS BLOGS EveryONE. 10 October 2023 (https://everyone.plos.org/2023/10/10/indigenous-data-sovereignty-and-open-data/, accessed 27 September 2024).
62. Regulatory Considerations on Artificial Intelligence for Health. World Health Organization; 2023 (https://iris.who.int/handle/10665/373421, accessed 27 September 2024).
63. Ethics and Governance of Artificial Intelligence for Health. World Health Organization; 2021 (https://iris.who.int/handle/10665/341996, accessed 27 September 2024).
64. Carroll SR, Garba I, Figueroa-Rodríguez OL, Holbrook J, Lovett R, Materechera S et al. The CARE principles for indigenous data governance. Data Science Journal 2020;19:43 (https://doi.org/10.5334/dsj-2020-043).
65. First Nations Data Governance Strategy. The First Nations Information Governance Centre (https://fnigc.ca/what-we-do/first-nations-data-governance-strategy/, accessed 13 March 2024).
66. First Nations Health Governance (https://www.fnha.ca:443/what-we-do/research-knowledge-exchange-and-evaluation/health-information-governance, accessed 13 March 2024).
67. Information Systems for Health (IS4H) (https://www.paho.org/ish/, accessed 13 March 2024).
68. Portela JVC. Artificial intelligence in Brazilian health and supplementary health services. Mattos Filho; 2024 (https://www.mattosfilho.com.br/en/unico/artificial-intelligence-health-services/, accessed 2 October 2024).
69. Qiu J. China plans to modernize traditional medicine. Nature 2007;446:590–591 (https://doi.org/10.1038/446590a).
70. Wang Y, Shi X, Li L, Efferth T, Shang D. The impact of artificial intelligence on Traditional Chinese Medicine. Am J Chin Med 2021;49:1297–1314 (https://doi.org/10.1142/S0192415X21500622).
71. Ayush sector all set to provide efficient, holistic, affordable and quality health services through 'Ayush Grid' and artificial intelligence. PIB Delhi; 2023 (https://pib.gov.in/PressReleaseIframePage.aspx?PRID=1917670, accessed 13 March 2024).

72. India to advance AI tools, establish AI policies for traditional medicine sector. OpenGov Asia; 2023 (https://opengovasia.com/2023/04/20/india-to-advance-ai-tools-establish-ai-policies-for-traditional-medicine-sector/, accessed 27 September 2024).
73. Tsumura: Traditional Medicine meets 21st century learning. L-TEN; 2023 (https://legacy.l-ten.org/focus/tsumura-traditional-medicine-meets-21st-century-learning/, accessed 13 March 2024).
74. Kanmuri K. Rational medicine and digital technology in Japan: connecting the silos. DIA Global Forum; 2022 (https://globalforum.diaglobal.org/issue/march-2022/rational-medicine-and-digital-technology-in-japan-connecting-the-silos/, accessed 27 September 2024).
75. Lee J, Lee M, Choi S, Kim Y, Koh B, Moon J. Strategic development plan of standardization on Korean medicine: comparison with traditional medicine policies between Korea and China. J Korean Med 2016;37:97–111 (https://doi.org/10.13048/jkm.16038).
76. Declaration of Astana. World Health Organization; 2018 (https://iris.who.int/handle/10665/328123, accessed 27 September 2024).
77. 2030 Agenda for Sustainable Development. ITU (https://www.itu.int:443/en/ITU-D/Statistics/Pages/intlcoop/sdgs/default.aspx, accessed 13 March 2024).
78. G20 primer on traditional medicine. RIS; 2023 (https://fitm.ris.org.in/sites/fitm.ris.org.in/files/Publication/FITM-G20-Primer-on-Tradition-Medicine.pdf, accessed 27 September 2024).
79. WHO benchmarks for the training of Ayurveda. World Health Organization; 2022 (https://iris.who.int/handle/10665/351480, accessed 2 October 2024).
80. Launch of the Traditional Medicine morbidity codes of Ayurveda, Siddha and Unani chapter in International Classification of Diseases (ICD) 11 as Module 2 (https://pib.gov.in/Pressreleaseshare.aspx?PRID=1994614, accessed 13 March 2024).
81. Thomas J. ICD-11 inclusion of Ayurveda, Siddha, Unani reclaims global health narrative. Policy Circle; 2024 (https://www.policycircle.org/society/icd-11-includes-ayurveda-unani/, accessed 27 September 2024).
82. Focus Group on Artificial Intelligence for Health (FG-AI4H). ITU (https://www.itu.int/en/ITU-T/focusgroups/ai4h/Pages/default.aspx, accessed 27 September 2024).
83. ITU – WHO FG-AI4H Topic Description Document for the Topic Group on AI for Traditional Medicine (TG-TM) (https://www.itu.int/en/ITU-T/focusgroups/ai4h/Documents/del/DEL10_23-TG-TM-A20230915-Prepub.pdf, accessed 14 March 2024).
84. WIPO member states adopt historic new treaty on intellectual property, genetic resources and associated traditional knowledge. WIPO; 2024 (https://www.wipo.int/pressroom/en/articles/2024/article_0007.html, accessed 27 September 2024).
85. Diplomatic conference to conclude an international legal instrument relating to intellectual property, genetic resources and traditional knowledge associated with genetic resources. World Intellectual Property Organization; 2024 (https://www.wipo.int/edocs/mdocs/tk/en/gratk_dc/gratk_dc_7.pdf, accessed 27 September 2024).
86. ISO/TC 215. Health informatics. ISO (https://www.iso.org/committee/54960.html, accessed 27 September 2024).
87. How AI drives innovation in healthcare. ISO (https://www.iso.org/contents/news/2023/04/ai-in-healthcare.html, accessed 27 September 2024).
88. Glickman ML. Health informatics and AI, the road to interoperability. ISO; 2022 (https://jtc1info.org/wp-content/uploads/2022/06/01_04_Michael_ISO_IEC_AI_Workshop-M-Glickman-0522-rev-1.pdf, accessed 27 September 2024).
89. ISO/TS 16277-1:2015. ISO (https://www.iso.org/standard/56044.html, accessed 13 March 2024).
90. ISO/TS 18790-1:2015. ISO (https://www.iso.org/standard/63381.html, accessed 13 March 2024).

Glossary of technology, non-technology and TM-related terms

1. **Acupuncture manipulation.** Movement of the needle applied after insertion to increase the effectiveness of acupuncture, basically including thrusting, lifting, twirling and rotating manipulations. (*1*)
2. **Artificial intelligence (AI).** A branch of computer science focused on creating programs capable of performing tasks that typically require human intelligence, such as learning, problem-solving and decision-making (*2,3*).
3. **AI benchmarks.** Comparative metrics and assessment frameworks specific to a particular use case used to appraise, certify or regulate the application of an AI model, system or tool in relation to that use case (*2*).
4. **AI in health care.** The field of knowledge and practice associated with the development and use of AI to improve health (*2*).
5. **AI lifecycle.** Typically involves several phases that include to: plan and design; collect and process data; build model(s) and/or adapt existing model(s) to specific tasks; test, evaluate, verify and validate; make available for use/deploy; operate and monitor; and retire/decommission AI systems. These phases often take place in an iterative manner and are not necessarily sequential. The decision to retire an AI system from operation may occur at any point during the operation and monitoring phase (*4*).
6. **AI systems.** A machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments. AI systems are designed to operate with varying levels of autonomy (*4*).
7. **Algorithm.** A final set of instructions (or rules) that defines a sequence of operations for solving a particular computational problem for all the problem instances for a problem set (*5*).
8. **Application of AI.** The practice of using AI to achieve a specific goal, such as enhancing health outcomes by improving medical diagnosis, data-based treatment decisions, digital therapeutics, clinical trials, and self-management of care (*2,3*).
9. **Ayush.** Includes traditional and indigenous systems of medicine, such as Ayurveda, Yoga and Naturopathy, Unani, Siddha, Sowa-Rigpa, and Homoeopathy (*6*).
10. **Biopiracy.** The unauthorized extraction of biological resources and/or associated traditional knowledge from developing countries or the patenting of spurious inventions based on such knowledge or resources without compensation (*7*).
11. **Clinical decision support systems.** Provides clinicians, staff, patients or other individuals with knowledge and person-specific information to enhance health and health care, and encompasses a variety of tools to enhance decision-making in the clinical workflow. These tools include computerized alerts and reminders to care providers and patients; clinical guidelines; condition-specific order sets; focused patient data reports and summaries; documentation templates; diagnostic support; and contextually relevant reference information (*8*).

12. **Complementary medicine.** Additional health care practices not part of a country's mainstream medicine. Evidence-based complementary medicine has the potential to supplement mainstream medicine and more comprehensively support people's health and well-being needs (*9*).
13. **Computer vision.** A scientific field that deals with how computers gain a high-level understanding from digital images or videos. From the perspective of engineering, it aims to automate tasks that the human visual system can do (*5*).
14. **Data mining.** Applying computational methods to large amounts of data in order to reveal new non-trivial and relevant information (*10*).
15. **Data sovereignty.** A group or individual's right to control and maintain their own data, which includes the collection, storage, and interpretation of data (*11*).
16. **Data stewardship.** Ensuring effective control and use of data assets, including creating and managing metadata, applying standards, managing data quality and integrity, and additional data governance activities related to data curation (*12*).
17. **Deep learning.** Also known as "deep structured learning", it is a subset of machine learning based on artificial neural networks or multi-layered models to progressively extract features from data (*3,13*).
18. **Developers.** Individuals, research organizations and companies involved in the design, deployment and updating of AI technologies (*3*).
19. **Digital divide.** Refers to the gap between demographics and regions that have access to modern information and communications technology and those that do not or have restricted access. This technology can include the telephone, television, personal computers and the Internet (*2*).
20. **Digital literacy.** The ability to understand and use information in multiple formats from a wide range of sources when it is presented via computers (*14*).
21. **Digital technologies.** Information and communication technologies that include the Internet of Things, virtual care, remote monitoring, artificial intelligence, big data analytics, blockchain, smart wearables, platforms, tools enabling data exchange and storage and tools enabling remote data capture (*2*).
22. **Digitization.** The process of changing data into a digital form that can be easily read and processed by a computer (*15*).
23. **Electronic health record (EHR).** A health record residing in an electronic system specifically designed for data collection, storage and manipulation, and to provide safe access to complete data about patients. Act as clinical decision support tools, offering important clinical information for the care of patients (*16*), and typically contain a patient's medical history, diagnoses and treatment, medications, allergies, immunizations, as well as radiology images and laboratory results (*17*).
24. **Frontier technologies.** Technologies emerging at the intersection of radical scientific breakthrough and real-world implementation, such as AI, big data, bioprinting and quantum computing (*18*).
25. **Good-quality data.** Data that meet predefined standards and encompass the following characteristics: relevance, credibility, accuracy, timeliness, punctuality, methodological soundness, coherence and accessibility (*19*).

26. **Herbal medicine.** Includes herbs, herbal materials, herbal preparations, and finished herbal products, that contain as active ingredients parts of plants, or other plant materials, or combinations (*20*).
27. **High-income countries.** Countries with a gross national income per capita exceeding US$ 14,005 in the 2025 fiscal year, according to the World Bank (*21*).
28. **Holistic health.** Health care that focuses on a person's experience of illness and takes into consideration the cultural, psychosocial and environmental determinants of health and well-being (*22*).
29. **Low- and middle-income countries.** Countries with a gross national income per capita less than US$ 14,005 in the 2025 fiscal year, according to the World Bank (*21*).
30. **Machine learning.** A field of computer science concerned with the development of models/ algorithms that can solve specific tasks by learning patterns from data rather than by following explicit rules (*5*).
31. **Natural language processing.** A form of AI that enables machines to understand human language (*3*).
32. **Performance optimization.** Modifications performed on the AI model, system or tool with the intention of improving its ability to perform as expected, using metrics such as accuracy, reliability and responsiveness (*5*).
33. **Policy-making.** The creation of a principle or a plan to guide decisions, actions and outcomes (*23*).
34. **Post-market surveillance.** A systematic process to collect and analyse the performance of and experience gained from the use of AI systems placed on the market to identify any need for corrective or preventive actions (*5,24*).
35. **Reusable knowledge base.** A repository containing knowledge stored for the purposes of reuse, sometimes referred to as a Knowledge Management System (*25*).
36. **Telemedicine.** Telemedicine supports the provision of health-care services at a distance; that is, the individual and health-care providers need not be in the same location. Telemedicine enables the delivery of safe and quality care to individuals living in areas with limited access to services (*26*).
37. **Traditional Medicine.** Codified or non-codified systems for health care and well-being comprising practices, skills, knowledge and philosophies originating in different historical, cultural contexts, that are distinct from and pre-date biomedicine, evolving scientifically for current use from an experience-based origin. It emphasizes nature-based remedies and holistic, personalized approaches to restore balance of mind, body and environment (*9*).
38. **Training data.** Data used for training an AI system through fitting its learnable parameters (*24*).

Glossary references

1. WHO benchmarks for the practice of acupuncture. World Health Organization; 2021 (https://www.who.int/publications/i/item/978-92-4-001688-0, accessed 14 April 2025).
2. Global strategy on digital health 2020–2025. Geneva: World Health Organization; 2021 (https://iris.who.int/handle/10665/344249, accessed 14 April 2025).
3. Ethics and governance of artificial intelligence for Health. World Health Organization; 2021 (https://iris.who.int/handle/10665/341996, accessed 27 September 2024).
4. Recommendation of the Council on Artificial Intelligence. OECD Legal Instruments. Paris: Organization for Economic Co-operation and Development; 2019 (OECD/LEGAL/O449; https://legalinstruments.oecd.org/en/instruments/OECD-LEGAL-0449#mainText, accessed 7 April 2025).
5. Generating evidence for artificial intelligence-based medical devices: a framework for training, validation and evaluation. Geneva: World Health Organization; 2021 (https://iris.who.int/bitstream/handle/10665/349093/9789240038462-eng.pdf?sequence=1, accessed 14 April 2020).
6. About us. In: Government of India Ministry of Ayush [website]. (https://ayush.gov.in/#!/aboutus, accessed 14 April 2025).
7. Robinson D. Confronting biopiracy: challenges, cases and international debates. Oxfordshire, UK: Taylor & Francis; 2010.
8. Clinical decision support [website]. US gov Assistant Secretary for Technology Policy (https://www.healthit.gov/topic/safety/clinical-decision-support, accessed 14 April 2025).
9. WHO global strategy on traditional medicine 2025–34 (under development).
10. Kallio A, Tuimala J. Data mining. In: Dubitzky W, Wolkenhauer O, Cho KH, Yokota H, editors. Reference encyclopaedia of systems biology. New York: Springer; 2013 (https://link.springer.com/referenceworkentry/10.1007/978-1-4419-9863-7_599, accessed 14 April 2025).
11. Data sovereignty. In: National Library of Medicine [website]; 2022 (https://www.nnlm.gov/guides/data-glossary/data-sovereignty, accessed 14 April 2025).
12. Data stewardship. In: National Library of Medicine [website]; 2022 (https://www.nnlm.gov/guides/data-glossary/data-stewardship, accessed 14 April 2025).
13. Regulatory considerations on artificial intelligence for health. Geneva: World Health Organization; 2023 (https://iris.who.int/handle/10665/373421, accessed 27 September 2024).
14. Gilster P. Digital literacy. New York: John Wiley & Sons; 1997:1–2.
15. Digitization. In: Oxford learner's dictionaries [website] (https://www.oxfordlearnersdictionaries.com/definition/english/digitization, accessed 14 April 2025).
16. Pan American Health Organization, World Health Organization. Electronic health records and interoperability: understanding two key concepts for a better public health response. Pan American Health Organization; 2020 (https://iris.paho.org/bitstream/handle/10665.2/52003/Factsheets-Digital_Health-EHR-Interoperability-eng.pdf?sequence=15, accessed 14 April 2025).
17. The global health observatory [online database]. World Health Organization (https://www.who.int/data/gho/indicator-metadata-registry/imr-details/4791, accessed 14 April 2025).
18. Frontier technologies. Geneva: World Intellectual Property Organization (https://www.wipo.int/export/sites/www/about-ip/en/frontier_technologies/pdf/frontier-tech-6th-factsheet.pdf, accessed 14 April 2025).

19. WHO glossary of health data, statistics and public health indicators. World Health Organization; 2024 (https://cdn.who.int/media/docs/default-source/documents/ddi/indicatorworkinggroup/glossary_of_terms_june-2024.pdf, accessed 14 April 2025).
20. Traditional, complementary and integrative medicine [website]. World Health Organization (https://www.who.int/health-topics/traditional-complementary-and-integrative-medicine#tab=tab_1, accessed 14 April 2025).
21. World Bank country and lending groups [database]. World Bank (https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups, accessed 14 April 2025).
22. People-centred health care: technical papers: International Symposium on the People-Centred Health Care: Reorienting Health Systems in the 21st Century, The Tokyo International Forum, 25 November 2007. World Health Organization Regional Office for the Western Pacific; 2008 (https://apps.who.int/iris/handle/10665/207004, accessed 7 April 2025).
23. Health in All Policies (HiAP) training slides: companion material to support HiAP training activities: Module 4 Part 2: Policy-making and HiAP [website]. World Health Organization; 2020 (https://www.who.int/publications/m/item/health-in-all-policies-(hiap)-training-slides-companion-material-to-support-hiap-training-activities, accessed 7 April 2025).
24. Article 3: Definitions. In: EU Artificial Intelligence Act [website] (https://artificialintelligenceact.eu/article/3/, accessed 7 April 2025).
25. Alavi M, Leidner DE. Review: Knowledge management and knowledge management systems: conceptual foundations and research issues. MIS Quarterly. 2001;25:107–36. doi:10.2307/3250961.
26. World Health Organization, International Telecommunication Union. National eHealth strategy toolkit. Geneva: World Health Organization; 2012 (https://iris.who.int/bitstream/handle/10665/75211/9789241548465_eng.pdf?sequence=1, accessed 14 April 2025).

World Health Organization
Avenue Appia 20
1121 Geneva 27
Switzerland