

The AI-Data Skills Framework

A Playbook for Policy-makers and
Government Stakeholders



Standardizing Skilling, Credentialling, and Measurement
Ecosystem for India's AI-Data Workforce

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Why AI-Data Skills Matter

This Playbook is designed to help policymakers and government stakeholders identify, measure, and credential a notable part of the AI talent in India — **the AI-Data workforce**. The AI-Data Skills Framework equips different stakeholders with a common vocabulary to name who these workers are and count them accurately, and credentialing pathways to recognize the skills and competencies they already have.

India's AI ecosystem is expanding rapidly, backed by significant public investment and a growing talent base. The IndiaAI Mission and Centres of Excellence for AI represent an investment of INR 10,300 crore over five years, while AI could contribute as much as USD 1.7 trillion to India's economy by 2035 (PIB, 2025). This growth also depends on a substantial human workforce that generates, annotates, enriches, validates, and maintains the data behind AI systems. India's data annotation and labelling workforce alone is projected to reach 1 million workers by 2030, with linguistic diversity creating further demand for language data and contextual expertise.



INR 10,300 CRORE
committed over five years to the IndiaAI Mission and Centres of Excellence for AI



USD 1.7 TRILLION
AI could potentially contribute to India's economy by 2035



16%
India's share of the global AI talent pool, nearly one in six AI professionals





This creates an opportunity to expand digital employment, including for workers in rural areas and Tier 2 and 3 towns. AI-data work already spans BPOs, technology companies, data platforms and social enterprises, with roles requiring different combinations of technical skills, domain knowledge and human judgement. However, systems for identifying, measuring, recognising and developing these skills have yet to fully keep pace with the market. Emerging AI-data roles are not adequately captured in existing labour statistics, curricula and competency frameworks, making it harder to recognise existing capabilities, understand workforce needs and build clearer pathways for progression.

The AI-Data Skills Framework (AISF) is a competency framework that provides a common language for this evolving landscape. It maps five AI-data worker personas across the AI Data value chain - Data Associate, Data Enricher, Data Auditor, Data Analyst, and Data Specialist, and the knowledge, technical skills, and behavioural skills associated with them.

For government and policy stakeholders, the framework offers two practical applications:

1. Skill recognition and credentials: connect emerging AI-data competencies with existing skilling and qualification systems.
2. Workforce measurement intelligence: strengthen how emerging AI-data work is identified and measured.



Who are AI-Data Workers?

The AISF represents AI-data workers who **prepare, check, annotate, validate, and maintain the data** that AI systems are trained and run on, validate and evaluate AI outputs, handle edge cases and exceptions, and inject domain-specific human context so the AI stays accurate, safe, and reliable.¹



In practice, AISF covers people who:

- Collect or generate data for AI training. For example, recording voice samples, photographing products, or filming everyday tasks ("egocentric" data collection) for training datasets.
- Label, annotate, or tag data to make it machine-readable by drawing bounding boxes, transcribing audio, categorizing images or text, and so on.
- Review, audit, or moderate AI outputs for accuracy, safety, bias, or policy compliance.
- Handle exceptions and edge cases that automated systems cannot resolve on their own, escalating or resolving them using human judgment.
- Structure, validate, or maintain the datasets used to retrain and improve deployed models.



Defining the AI-Data Workforce: The AISF focuses on the AI-data workers as their knowledge, skills, and attributes are distinct enough from engineers' and people managers' to warrant a professional identity of their own. This recognition is the necessary first step before that identity can be built into India's broader economic and educational systems.

OUTSIDE OF SCOPE

Machine Learning Engineers, Data Scientists, and other AI specialists who focus on the engine: writing code, designing algorithms, building computational infrastructure, and optimizing models for raw capability, speed, and scale. The hand-offs between these roles are iterative and, at times, fluid, which makes strict boundaries hard to draw. However, both are essential to building AI, as they address two different sides of the same equation. AI data workers supply the foundational reality and ethical logic the architecture processes, relying on human cognitive and contextual judgment to translate reality into actionable logic for AI systems that ML engineers and Data Scientists build. High-level technical engineering roles depend as much on the human judgment, domain expertise, and data validation the AI-data workforce provides as they do on code.

1 Ferrone et al. (2026) describe AI work as organized into three tiers: (I) innovators, who build the underlying AI infrastructure and models; (II) facilitators, who deploy, integrate, and maintain AI capability for practical use; and (III) users, whose work is altered by applying AI. Facilitators are a broad family of roles which includes "data facilitators" i.e., data architects, engineers, annotators, curators, and data-quality specialists, as a specific sub-category responsible for making data usable for AI systems. AI-data workers, as defined in the AISF, are this sub-category.





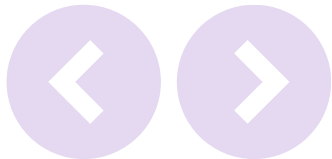
The Framework at a Glance

The AISF standardizes competencies across roles, tasks, and data modalities. It is reinforced by global industry and policy frameworks, most notably DigComp 3.0, SFIA, and IEEE, reflecting the layered, distributed nature of the AI industry itself.

It rests on the following core parameters:

- **Knowledge (“Knowing”)**: Measures theoretical and domain understanding. Domain requirements remain open-ended to accommodate specific modalities (e.g., medical vs. general text), but explicit functional and digital literacy baselines are established for every level.
- **Technical Skills (“Doing”)**: Measures manual, digital, and cognitive dexterity across tools and platforms. Written in strict DACUM syntax (Verb + Object + Qualifier) to emphasize movement and action
- **Transversal & Behavioral Skills (“Interpersonal & Operational”)**: Captures professional conduct, self-management and regulation, platform navigation, data security, and ethics.
- **Accountability & Complexity (“Contextual Weight”)**: Evaluates scope of impact, burden of consequences, cognitive load, ambiguity, and autonomy to determine the final NSQF/NCrF level assignment.

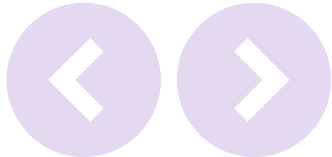
The AISF maps the AI-data value chain across five professional personas, each defined by a “Human Advantage,” i.e., the capability that continues to make human labour valuable. Each persona is mapped to an NSQF/NCrF band (instead of a single level), because progression in AI-data work is layered and iterative, and is not strictly linear. Table 1 provides a snapshot of the personas and their competencies, and identifies opportunities for policy stakeholders to bridge gaps in the skilling infrastructure.



Persona	Human Advantage in AI Data Value Chain Phase*	NSQF / NCrF	Opportunity & Gaps	What actions can policy and regulatory entities take?
Data Associate 	Collects or generates real-world data to establish “Ground Truth” at the Data Generation stage	Level 2.5–3.0 (Grade 10–12 / Early Vocational Certificate)	This persona offers women a flexible, low-barrier entry into digitally-embedded livelihoods, but piece-rate gig work risks precarity and instability. Corresponding role not found in NQR. Closest is ‘Data Entry Operator’	RPL deployment: Rapid deployment of Recognition of Prior Learning (RPL) programs can transform invisible, informal piece-rate workers into statistically recognised ‘AI-Data associates’
Data Enricher 	Maps chaotic reality into machine-readable taxonomies with precision as Dataset moves from Generation → Model Training	Level 4.0 (Higher Secondary Vocational / Undergraduate Entry)	Commonly associated with the "Data Annotator" role (already exists on NQR), encompasses the spectrum of data labelling and annotation roles in AI training. Requires sustained focus but is often managed with high-turnover, low-touch methods.	Micro-credentials: Best served by providing micro-credentials and formal training at scale, trackable by region, enterprise, language, and labour configuration. Skilling bodies (SSC-NASSCOM, NSDC) can align curricula directly to the technical skills identified under this persona.
Data Auditor 	Resolves grey areas using empathy, sarcasm detection, cultural nuance as Dataset moves from Generation → Model Training	Level 4.5–5.0 (Advanced Diploma / B.Voc / Undergraduate Degree)	Central to risk mitigation and is the frontline defence against AI hallucinations, toxicity, and systemic bias. Includes AI Data Quality Manager, Content Moderator, AI Quality Analyst etc. Most likely to progress along an enterprise's people-management track. No equivalent accredited course exists on the NQR — a clear Q-File gap.	Advanced credentialing: Regulators should use this persona to develop advanced credentialing pathways critical for national AI sovereignty, ensuring global models comply with local cultural and legal standards.

Persona	Human Advantage in AI Data Value Chain Phase*	NSQF / NCrF	Opportunity & Gaps	What actions can policy and regulatory entities take?
Data Analyst 	Identifies systemic logic failures or drift as datasets move from Model Training → Model Maintenance	Level 5.5–6.0 (Professional Bachelor's Degree / Post-Graduate Diploma)	Operational bridge between the annotators and the ML engineers. Responsible for fixing dataset logic failures and throughput bottlenecks, but rarely hold the administrative authority to alter underlying engineering architecture Data Analyst and AI-Data Quality Analyst already on the NQR.	Higher-Ed Integration: Embed into data science/analytics degree curricula to build the AI ecosystem's "middle-management" layer.
Data Specialist 	Deconstructs professional wisdom into modular reasoning chains for autonomous agents as datasets move between Model maintenance → Dataset Refinement or Development → Model Training	Level 6.5–7.0 (Master's Degree / Expert Professional)	Enterprises depend on this persona to deconstruct professional wisdom into modular reasoning chains that autonomous agents can emulate. Includes those (1) who guide the strategic direction of datasets for model development and maintenance and (2) domain experts who train the agent or model for targeted use cases, by breaking down their knowledge into rigid, sequential Chain of Thought logs. No equivalent accredited course exists on the NQR — a clear Q-File gap.	National Standards & Auditing: Engage this tier to draft national standards, audit public-sector AI deployments in sensitive welfare sectors, and ensure AI systems in critical areas (healthcare, education, finance) adhere strictly to legal frameworks like the DPDP Act.

For a complete breakdown of the knowledge, technical, and behavioural competencies under each persona, and how they map onto the data value chain, see [AI-Data Skills Framework \(AISF\)](#).



Notes on Reading the Framework

BANDED MAPPING

Roles map to NSQF bands instead of rigid single levels. For example, a Language Data Associate recording basic colloquial audio operates at a lower NSQF level than a Healthcare Data Associate recording responses to clinical queries, even though the core task of audio recording is similar.

SPECIALISED VS. LINEAR PROGRESSION

Progression in AI-data work is rarely linear. Workers advance along two main tracks: a Domain Specialisation track and a People and Operations Management track (moving from individual contributor to leadership roles).

PSYCHOLOGICAL AND OPERATIONAL VALUE OF PERSONAS

Replacing transactional terms like “click-worker” with professional titles such as “Data Associate” provide workers a clear way to describe their expertise. Personas can also enable empathy-based training design: a facilitator can ask concretely, “What tools does the Data Auditor struggle with?” instead of addressing technical gaps in the abstract.



A detailed breakdown of the knowledge, technical, and behavioural skills for each persona is provided in the companion reference, AI-Data Skills Framework (AISF).





Putting AISF into Practice

A Roadmap for Policymakers, Skilling Bodies and Regulators

For national governments and multilateral institutions, the rapid expansion of the AI-data value chain presents a critical governance challenge: millions of workers are powering the AI economy, yet this work is not adequately captured by existing labour statistics. The AISF offers a robust, evidence-driven policy instrument to formalize this Human-in-the-Loop (HITL) workforce by providing a standardized, task-aligned taxonomy that bridges grassroots digital labour and national regulatory architecture.

The persona-level recommendations in the Framework Snapshot above are the starting point.

Beyond them, there are two policy and system-level levers:

- 1) providing portable credentials by mapping the AISF onto national skilling frameworks
- 2) reforming how national statistics measure and count this workforce.



1. Recognise and credential AI-data skills

Align AISF with the NSQF, NCrF and existing skilling infrastructure

India's educational and vocational ecosystem is shifting from input-heavy models toward Competency-Based Education and Training (CBET), anchored by the NSQF, which organises qualifications across thirteen levels based on five core parameters: theoretical knowledge, technical skills, transversal skills, responsibility, and complexity. While the NSQF provides a robust architecture for traditional professions, it does not currently account for the AI data workforce — whose fluid, platform-mediated, and contractually ambiguous work arrangements do not map onto legacy occupational definitions or codes.

HOW DO WE RECOGNISE AND CREDENTIAL EXISTING SKILLS?

- Initiate Recognition of Prior Learning (RPL) programs immediately. Deploy RPL assessments based on AISF personas to validate lived experience and grant a portable professional identity without requiring redundant training.
- This is most urgent for the Data Associate and Data Enricher tiers (NSQF Level 2.5–4.0), which concentrate the largest share of informal workers and where accredited baseline courses (Data Entry Operator and Data Annotator) already exist on the National Qualifications Register (NQR).



HOW DO WE BUILD ACCREDITED COURSES FOR EMERGING ROLES?

- Facilitate partnerships with standard-setting bodies, such as the IT-ITeS Sector Skills Council NASSCOM, to translate the competency-based AISF into official National Occupational Standards (NOS) and navigate the NCVET Q-File audit process.²
- The clearest gap exists at the Data Auditor and Data Specialist tiers, where no equivalent accredited courses currently exist on the NQR.

HOW CAN WE ENSURE CREDIT PORTABILITY AND CAREER GROWTH?

- Institutionalize the AISF within the **Skill India Digital Hub (SIDH)** and connect it to the **Academic Bank of Credits (ABC)**.³
- For the **Data Analyst** tier (Level 5.5–6.0), this chiefly means banking existing higher-education degrees; for the **Data Specialist** tier (Level 6.5–7.0), it means using the AISF to establish national standards for sensitive public-sector AI deployments.
- There is sparse empirical evidence of longitudinal progression from grassroots tiers (Associate, Enricher, Auditor) into the Data Analyst tier, which currently requires a formal undergraduate degree. By using the NCrf to bank micro-credentials earned at lower tiers, this approach could create alternative pathways by allowing workers to accumulate credentials and receive recognition for relevant skills and experience alongside formal qualifications.



2. Identify and Measure AI-data work through National Statistical Instruments

Strengthen how emerging AI-data roles are captured in labour statistics.

National statistical instruments such as the **Periodic Labour Force Survey (PLFS)** are currently not adequately equipped to capture the realities of the modern AI-data economy. Relying on legacy classification systems (NCO-2015 and NIC-2008), official surveys are often not able to capture the distinct, micro-tasked nature of AI-data refinement. Data labeling has no dedicated NCO-2015 code, and platform-mediated piece-rate work escapes standard workplace-location code and assignment to a single enterprise type.

This statistical blind spot is particularly acute for women performing gig work in the AI-data value chain. Take the example of "**egocentric data collection**," which involves women mounting a smartphone on their head to film themselves cooking, cleaning, or watering plants for AI training datasets. From an enumerator's perspective, this work looks identical to unpaid domestic chores. and slips through standard activity enumeration blocks.

2 Formally recognising a credential within India's skilling ecosystem requires a Qualification File (Q-File) approved by NCVET and uploaded to the National Qualifications Register (NQR). This process is currently lengthy and lacks standardised vocabulary for emergent AI roles. By categorising the AI-data workforce into distinct personas and mapping their tasks to the five NSQF parameters, the AISF provides Awarding Bodies with the blueprint required to draft successful Q-Files.

3 Under the National Credit Framework (NCrF), learning outcomes are “banked” using the APAAR ID (Automated Permanent Academic Account Registry) and stored in the Academic Bank of Credits (ABC), which functions as the national repository for competency credits and credentials.





“ *I had told my husband that he should pay me for doing housework like washing dishes, washing clothes, and cleaning the house. He said, 'It is your own house, you are doing your own work.' Later, when this work came, I told him, 'See, you did not value this work, but Myna did. They thought this work has value and paid for it.*
— **45-year-old gig worker, Female, Myna Mahila Foundation**

Men and women training and maintaining advanced AI models from India’s small towns are rarely visible in the national discourse or in the global AI value chains. Within formal delivery/BPO centers in Tier 2/3 towns, full-time salaried workers perform complex semantic annotation, cataloguing, and deal with edge cases that do not fit standard operating procedures. In measurement systems, they are usually lumped into generic legacy categories like "Data Entry Operators" or "E-commerce Support workers”.

“ *The algorithm is doing the work; the algorithm is giving the instructions.... But manually, we need to check whether it is an exact match or not...If everything is exact and the algorithm is correct, then there is no need for work for us. We actually don't need to be here in this company. So, however much AI is implemented, humans must be there to give instructions to machines or whatever it may be.*
— **late 20s, Quality Controller, Female, NextWealth**

Thus, existing national surveys do not adequately capture AI-data work as a distinct form of skilled work, partly because of how gig work is self-reported and how emerging roles map onto existing occupational codes. AISF could help address this measurement gap by providing a task- and competency-based framework for identifying and classifying AI-data work.



HOW DO WE CAPTURE PLATFORM-BASED GIG WORK AND AI-DATA MICROWORK IN STATISTICS?

- **Investigator Calibration via the Subsidiary Block:** National survey investigators can be trained to deploy the PLFS subsidiary activity block (Block 5.2) more systematically. Rather than accepting passive self-reports, investigators can use the AISF's proficiency tiers to actively probe for secondary, platform-based gig work, ensuring that home-bound data generation and micro-tasks are formally enumerated.
- **Mapping Task Categories to NCO-2015:** Policymaking bodies can advocate for the immediate adoption of NCO-2015 at the unit level, developing a formal technical crosswalk between the AISF's granular task matrices and the finer unit-level sub-categories of NCO-2015. This will allow complex, emerging tasks to map cleanly to official industrial codes.

HOW TO CAPTURE AI-RELATED SKILLS AND WORK IN A GRANULAR WAY?

- **Supplementary AI Labour Module:** Mirroring how Block 4.1 of PLFS handles vocational training, the government could look to institute a dedicated supplementary module within the PLFS, specifically for digital and AI-related work. This module is envisioned to employ the AISF's standardized task definitions to systematically record platform intermediaries, specific task types, variable working hours, and piece-rate earnings data.





Way Forward

Millions of workers possess technical skills and knowledge gained through platform-mediated and BPO-based AI-data work. Yet, their APAAR IDs do not exist, and their ABC accounts are empty due to a lack of institutional validity. The AISF provides the diagnostic scaffolding required to activate Recognition of Prior Learning (RPL) and On-the-Job Training (OJT) programs at scale, depositing verifiable credits directly into workers’ digital accounts, and transforming “ghost labour” into portable professional identities.

The AISF offers two concrete and complementary levers to close the gap: strengthening pathways for skills recognition and credentialing through alignment with the NSQF and NCrF, and improving the measurement of AI-data work within national labour statistics. Credentialing can provide formal recognition of workers’ skills, while improved measurement can strengthen understanding of the scale, composition and characteristics of the workforce. The two levers together can support more comprehensive policy and ecosystem approaches to emerging AI-data work.

The persona-level detail in the Framework also highlights the need for differentiated pathways for skills recognition and development, instead of a one-size-fits-all approach. For instance, a Data Associate may need an OJT (on-the-job) or RPL intervention, but a Data Auditor, or Data Specialist may need incremental micro-credentials that signal to industry the degrees of accountability and complexity they navigate to deliver a seamless experience with AI.



This agile approach is what will turn a competency framework into an implementable policy instrument, allowing not just the skilling of AI-data workers but also validating the existing pool of skilled AI-data workers.

Importantly, these pathways can build on existing institutional infrastructure. The Skill India Digital Hub, Academic Bank of Credits, and PLFS provide established mechanisms for skills recognition, learning, and workforce measurement. AISF offers a common taxonomy that could help institutions such as NCVET, NASSCOM and the National Statistical Office identify and respond more consistently to emerging AI-data roles and competencies within their respective mandates.



Related Resources

1. [Webpage](#)
2. [Toolkit | September 2026](#)
3. [Worker Experience Report \(Forthcoming\)](#)

APPROACH | HOW AISF WAS DEVELOPED

The AISF is the outcome of an intensive, voluntary consultation with AI-data enterprises and their workers in India, conducted through DACUM (Developing A Curriculum) workshops, Key Informant Interviews, and In-Depth Interviews with 43 participants across three organisations: **NextWealth Entrepreneurs Pvt. Ltd.** (a BPO/KPO with salaried employment contracts), **Myna Mahila Foundation** (a non-profit with a crowdsourcing structure for gig and micro-work), and **Karya** (DAIA Tech Pvt. Ltd., a platform-based social enterprise sourcing workers through community organisations and self-help groups). The research was anchored by LEAD's Gender x Digital (GxD) hub and approved by IFMR's ethics committee.





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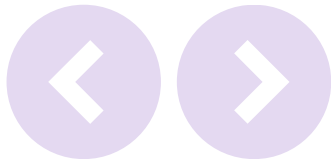
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Annexure: Benchmarking Global Frameworks

To ensure international compatibility without sacrificing local relevance, 33 global artifacts were systematically evaluated across three categories:

- Digital Competency Frameworks: SFIA 9,⁴ DigComp 2.2/3.0,⁵ UNESCO AI Frameworks,⁶ ETS Skills Taxonomy.
- Policy & Standards: IEEE P7015,⁷ UNESCO Civil Servant AI Competencies, Gov.UK AI Skills Package.
- Pilots & Field Research: LUMS Framework, Gender x Digital (GxD) hub, EQUALS Her Digital Skills.

ASSESSING GLOBAL FRAMEWORKS FOR THE INDIAN CONTEXT

Paradigm	Model	Misalignment with Domestic Realities
Professional-Corporate	SFIA 9	Assumes corporate hierarchies, direct managerial oversight, and individual workplace autonomy.
Citizen-Centric	DigComp 2.2 / 3.0	Assumes a "one-person, one-device" model with stable, high-speed connectivity.

⁴ Skills Framework for the Information Age (SFIA) 2025

⁵ DigComp 2.2 2024-2026, Cosgrove and Cachia 2025





These models inadequately reflect the realities of the workforce in the Global South along three key areas:



**MISINTERPRETING
AUTONOMY**

SFIA assumes managerial autonomy; in peri-urban and rural settings, a woman worker's autonomy is often circumscribed by social norms (e.g., household permission to participate) rather than corporate structures.

**DEVICE HARDWARE
ASSUMPTIONS**

Frameworks like DigComp assume single-user devices, failing to account for shared family phones, intermittent connectivity, and mediated digital access.

**LITERACY VS.
READINESS**

As highlighted by IEEE P7015, a clear distinction must be made between Literacy (knowing how to use a device) and Readiness (having the structural, financial, or social autonomy to perform work).

The AISF contextualizes these global standards, providing Indian regulatory authorities with a localized, task-aligned standard that can interface confidently with international bodies.

6 UNESCO 2024
7 IEEE, 2025





Acknowledgements

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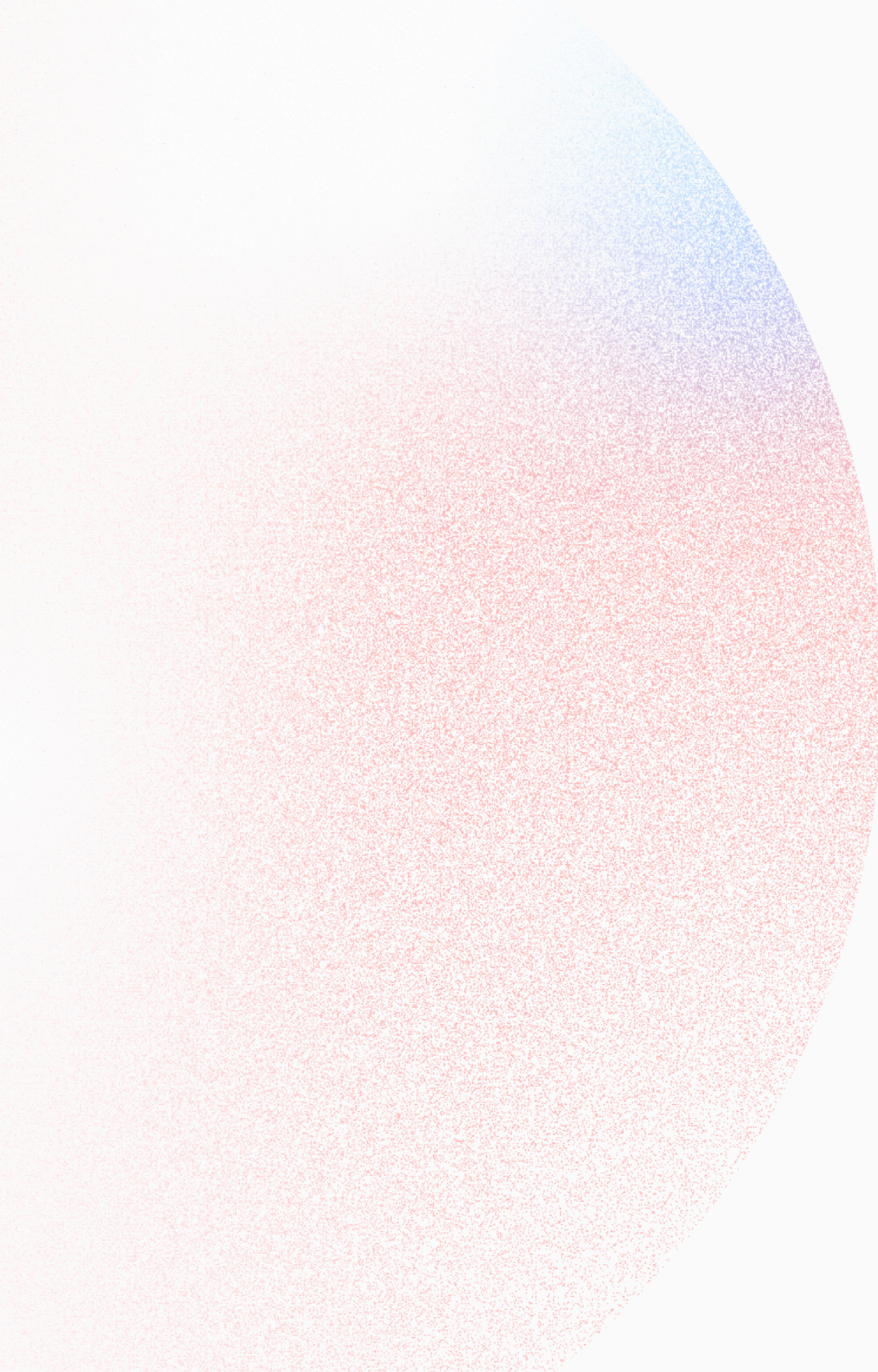
Most importantly, we thank the AI-data workers across NextWealth and Myna Mahila whose knowledge and experience this framework seeks to make visible and credential.

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Illustrations used were developed using AI-assisted tools, with human input and refinement.





The AI-Data Skills Framework (AISF) builds on The/Nudge's Common Digital Skills Framework (CDSF) and is part of Sanmati 2.0, a collaboration between the Gender x Digital (GxD) hub and The/Nudge exploring women's participation and opportunities across India's evolving digital value chain. GxD hub is an initiative of LEAD at Krea University (IFMR).



www.gxdhub.org



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