



Data for Decisions to Expand  
Nutrition Transformation

A landscape of trends and  
opportunities in nutrition data  
innovations

Jan 2022



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# Executive Summary

# This work aims to conduct a landscape analysis of trends and opportunities for nutrition data innovations

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## Objectives

- **Primary:** Start a conversation among donors, governments, and development partners in low- and middle-income countries (LMICs) about emerging solutions to data challenges and potential investments in nutrition data innovations
- **Secondary:** Contribute to broader awareness in the nutrition community of data innovations and their potential applications for nutrition data value chain (DVC) strengthening







## Scope Inclusion

- **Data innovations** which use new or non-traditional data sources, methods, and partnerships to reframe issues and generate new solutions to existing nutrition data challenges
- Data innovations under the following nutrition data domains – **nutrition status, diet, food security, food environment, food fortification, and micronutrient status**
- Created **in or after 2015**

## Methods

- We reviewed innovation **repositories, grey literature, and investment portfolios and held stakeholder consultations**
- The aim was to provide a snapshot of overall trends in data innovations for the nutrition domains listed above, not to create an exhaustive inventory of all innovations

We identified 9 data innovation categories influencing one or more parts of the DVC which we used to map nutrition data innovations found and explore potential opportunities

	<u>Prioritization</u> 	<u>Creation &amp; Collection</u> 	<u>Curation</u> 	<u>Analysis</u> 	<u>Translation &amp; Dissemination</u> 	<u>Decision Making</u> 
<b>Indicator development</b>						
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# Key findings from our review of nutrition data innovations include (1/2):



## **Key Finding 1: There has been a significant number of nutrition data innovations since 2015**

- The majority of innovations found related to the nutrition status or diet data domain
- When mapped to the DVC, most innovations related to the data creation, analysis, and translation stages, and comparatively fewer around prioritization or decision making



## **Key Finding 2: The majority of nutrition data innovations found are mobile solutions, artificial intelligence, or digitalization**

- Mobile solutions are increasingly being used to collect real-time data across several nutrition domains
- Artificial intelligence, a way to process large amounts of data, is being used to support clinical decisions for malnutrition diagnosis and estimate prevalence of food security or malnutrition
- Digitalization is helping to streamline or automate the process of collecting, storing, analyzing, and/or sharing data on nutrition status, dietary intake and compliance with fortification



# Key findings from our review of nutrition data innovations include (2/2):



## **Key Finding 3: Nutrition data innovations have started to bring solutions to fundamental data challenges, but there is more work to do given challenges remain**

- For example, within the micronutrient domain, modeling and simulation tools have helped to provide estimates of micronutrient deficiencies in the absence of primary data, however there is still strong demand from country stakeholders for original data collection on micronutrient status



## **Key Finding 4: Data innovations from other sectors can be leveraged to strengthen nutrition data value chains**

- Geospatial data and statistics, citizen-generated data, and artificial intelligence are examples of three innovation areas used by other sectors that have clear applications for nutrition
- Data partnerships and collaboratives for nutrition must be further explored, including how nutrition stakeholders can more actively participate in the broader data innovation space



## **Key Finding 5: The use of data innovations by nutrition stakeholders has accelerated during the COVID-19 pandemic in response to unique data challenges**

- Nutrition data innovations have emerged across the data value chain during COVID-19, but most efforts have focused on using mobile solutions for remote data collection and the use of data visuals to facilitate data translation



Scaling innovations requires an ecosystem of actors speaking to each other including funders, adopters, end users, and innovators. Our key recommendations are tailored to these groups:

**For innovation adopters:**  
governments and development partners



Identify and prioritize data gaps and challenges and then map to potential solutions—**consider leveraging both existing data sources and methods as well as innovations.**



**Learn from innovations that have been scaled successfully** in other contexts. Also consider tapping into innovations being scaled in the data space more broadly.

**For innovation funders:**



**Take a more strategic approach to investments in innovations** to fill gaps in the nutrition DVC, including consideration of pathways to scale and funding plans.



**Collaborate and coordinate efforts with other stakeholders** with possible co-funding of specific data challenges or types of innovations.



**Identify promising innovations that have successfully scaled across several geographies** to identify critical ingredients needed to scale up innovations.

Equally important is to increase nutrition data innovation awareness and literacy among key stakeholders so they are aware of and understand the tools available and their utility.



# Stakeholders pursuing nutrition data innovations should evaluate feasibility and weigh potential risks

## Feasibility

### Capacity

- ✓ Do **capacities** exist within countries to support and maintain data innovations?
- ✓ Is the data innovation particularly complex and is the **required technical expertise** readily available?

### Cost

- ✓ What are the **costs**?
- ✓ Is **funding** available to cover costs in the short and long term?

### Inputs

- ✓ Are **large quantities of data required** as an input? Are these data readily available?

## Risks

### Existing systems

- ✓ Could adoption or scale up of the innovation **stress existing systems and processes**?

### Data privacy

- ✓ What are the potential risks to **data privacy or security**?

### Data quality & equity

- ✓ Is the data produced of **high quality and representative** of the population?
- ✓ Could the innovations **exclude portions of the population** due to insufficient data availability or underlying bias in backend data used to power innovations?

# Goals & Approach

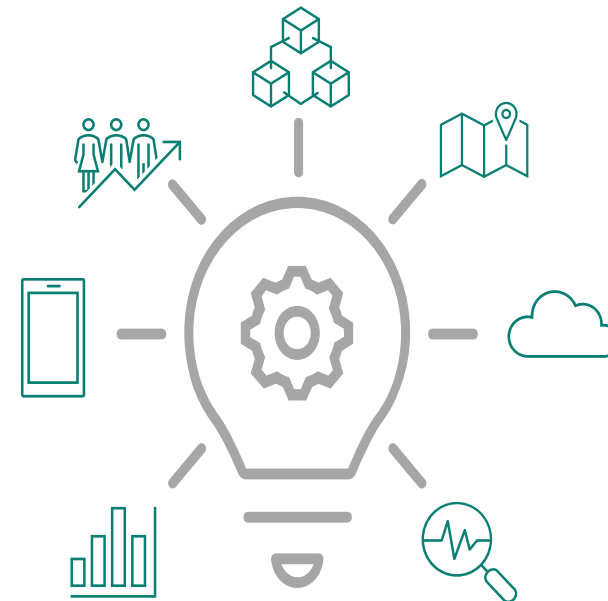
# Nutrition data innovations hold promise for strengthening the nutrition data value chain across LMICs

## Example Challenges



- **Prioritization:** Data gaps exist across nutrition domains including WHA target progress, intervention coverage, etc.
- **Collection:** Lack of real-time data and high cost of some data collection
- **Curation:** Limited systems interoperability which prevents analysis across multiple datasets
- **Analysis:** Lack of tools to derive insights and display information for decision-making

## Opportunity



“Data and the digital revolution are bringing better data, better tools, better data analytics, allowing us to be better informed, but that technology is rapidly outpacing the ability of the development community to adapt to its capabilities.”\*

# This work aims to conduct a landscape of trends and opportunities for nutrition data innovations

## Objective

**Primary:** Start a conversation among donors, governments, and development partners in LMICs about emerging solutions to data challenges and potential investments in nutrition data innovations

**Secondary:** Contribute to broader awareness in the nutrition community of data innovations and their potential applications for DVC strengthening

## Scope of Work

### Definitions

- **Data Innovation:** use of new or non-traditional data sources, methods, and partnerships to reframe issues and generate new solutions to existing nutrition data challenges\*
- **Nutrition Data Innovation:** data innovations which strengthen the nutrition DVC

### Exclusion

- Innovations created before 2015 since this was a key year after which substantial investments began to take place in the innovation space\*\*
- The expansion of existing nutrition data sources, methods, and partnerships to new contexts
- Innovations pertaining to nutrition sensitive data as well as data on basic or underlying determinants of nutrition

### Limitation

- This is **not a comprehensive review** since the purpose was not to provide an inventory of all nutrition data innovations, but rather a snapshot of overall trends

\*Definition adapted from IDIA, UNDP, and UN Global Pulse sources

\*\*A few innovations created prior to 2015 have been included as they were determined by the team to be considered key innovations in the space

# We first used a three-step approach to explore the broader data innovation space



## Step I: Scope definition

- a** Data innovations considered were -
1. **Innovative** according to our definition & scope
  2. **Frequently** mentioned in the literature or during expert consultations



## Step II: Data collection

- b** **Reviewed innovation repositories** such as the Global Innovation Exchange – the largest database of development innovations connecting innovators with funding and exposure opportunities, and **grey literature** such as reports, conference proceedings, UN documents and websites, & blogs\*
- c** **Held stakeholder interviews** to validate our findings and identify which innovations in the broader innovation space have the potential to make the biggest difference (overall and for nutrition)



## Step III: Data Extraction & Analysis






- d** **Organized the broader data innovation space into categories and sub-categories**, defining terminology and investigating which part of the nutrition DVC they influence
- e** Used the categories to:
- **Map nutrition data innovations**
  - **Explore current applications and potential opportunities** for nutrition to better leverage certain data innovation categories

\*Note - relevant peer reviewed literature was reviewed as needed but was not the focus of our search

# We used a similar but separate process to scope for nutrition data innovations



## Step I: Scope definition

- a** Data innovations within the following domains were included-
-  **Nutritional status data** including anthropometry and outcomes related to the World Health Assembly nutrition targets. *(Did not include overnutrition and diet related NCDs)*
  -  **Dietary intake data**
  -  **Food fortification data**
  -  **Food security & food environments data** including availability, access, affordability, & advertising
  -  **Micronutrient status data** including biomarkers and intake
- b** Nutrition data innovations which stemmed from/were adapted to address data challenges related to the **COVID-19 pandemic**



## Step II: Data collection

- c** **Innovation repositories** such as the Global Innovation Exchange
- d** **Internet search** including review of **grey literature** such as reports and blog posts from the UN and other nutrition-focused organizations as well as **investment portfolios** of innovation funders (e.g., World Bank)
- e** **11 stakeholder interviews** held around
- Gaps in the nutrition data space
  - Nutrition data innovations they are funding/ supporting
  - Nutrition data innovations they find groundbreaking



## Step III: Data Extraction & Analysis

- f** **Extracted the following information** for relevant nutrition data innovations
- Name
  - Brief description
  - Funder
  - Stage of scaling
  - Geography
  - DVC stage influenced
  - Data innovation category
  - Created or adapted during the COVID-19 pandemic
- g** **Complemented desk review findings with stakeholder inputs** especially around
- Gaps in the nutrition data space
  - Nutrition data innovations not captured during the desk review
  - Potential of data innovations more broadly for nutrition

# Setting the scene: Trends in the data innovation space

# To set the scene for this work, we identified 9 data innovation categories based on our scoping review

## Indicator development

- De novo indicators
- Proxy indicators
- Composite indicators

## Citizen-generated & open data

- Citizen-generated data
- Open data
- Crowdsourcing

## Mobile solutions

- Data collection tools
- Wearable devices
- Case management apps
- Diagnostic & clinical decision support apps

## Modeling & simulation tools

- Economic optimization modeling
- Health impact modeling
- Policy impact modeling

## Digitalization

- Electronic health records
- Blockchain

## Geospatial data & statistics

- Remote sensing
- Geospatial mapping
- Geographic information system/spatial statistics

## Artificial intelligence

- Machine learning
- Deep learning
- Natural language processing
- Computer vision

## Data visuals

- Scorecards
- Dashboards
- Index
- Profiles







## Data collaboratives & partnerships

- Data collaboratives
- Data partnerships

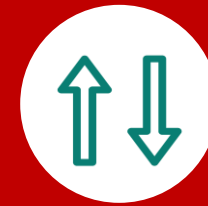
Big data is often embedded within these categories. Big data (in terms of large complex datasets) may be derived from mobile solutions, geospatial data, health records, etc., and is often processed using artificial intelligence or visualized by data visuals.



# These data innovation categories have the potential to influence one or more segments of the data value chain

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# Indicator development



**Description:** New measures and metrics that provide information on a particular topic

Sub-categories	Definitions	Application(s) to nutrition
<b>De novo indicators</b>	The creation or design of a new measure to capture information about a given topic	<ul style="list-style-type: none"> <li>To collect critical information on nutrition topics that lack common definitions for measurements. <b>Example:</b> <u><a href="#">Developing metrics to assess advocacy efforts</a></u></li> </ul>
<b>Proxy indicators</b>	The adoption of an indirect measure for an indicator of interest that is strongly correlated to this indicator, normally used when direct measures are unavailable or data on the topic is particularly limited <sup>1</sup>	<ul style="list-style-type: none"> <li>To illustrate a trend in nutrition when no direct measure exists or becomes difficult to collect. <b>Example:</b> <u><a href="#">Global Monitoring of School Meals as proxy for food insecurity</a></u></li> </ul>
<b>Composite indicators</b>	The combination of multiple indicators into one “index” to summarize a topic that is too complex to be measured with a single indicator <sup>2</sup>	<ul style="list-style-type: none"> <li>To provide a meaningful summary measure of a nutrition-related construct (e.g., calculating child diet quality by looking at breastfeeding and food group intake). <b>Example:</b> <u><a href="#">Composite indices for anthropometric data quality</a></u></li> </ul>

Note: When possible, slides 18-26 provide existing examples from nutrition in the “application(s) to nutrition column. These applications are meant to be illustrative and not exhaustive. References for category and sub-category definitions are available in Annex 4 indicated by numerical in-text citations.

# Citizen-generated & open data



**Description:** Data sourced directly from individuals in a population who voluntarily report; data that are freely used, shared, and aggregated together for public value

Sub-categories	Definitions	Application(s) to nutrition
<b>Citizen-generated data*</b>	Data produced by non-government actors under the consent of citizens to monitor, demand, or drive change on social issues; aims to reflect a diverse population and often requires relationship building, training, and ongoing engagement <sup>3,4</sup>	<ul style="list-style-type: none"> <li>To gather data on access to and quality of nutrition services directly from community members. <b>Example:</b> <a href="#"><u>Citizen H2D3</u></a></li> </ul>
<b>Open data**</b>	Data that is made freely available and can be used, shared, and re-used for any purpose with minimal or no restrictions, often published as part of transparency and accountability efforts by public sector institutions <sup>5,6</sup>	<ul style="list-style-type: none"> <li>To use program data for planning or advocacy by civil society organizations or media. <b>Example:</b> <a href="#"><u>INDEXX24 Global Food Matter Database</u></a></li> </ul>
<b>Crowdsourcing</b>	Gathering data (e.g., opinions, ideas) or calling for the completion of tasks from the general public typically through the Internet in an unstructured approach that can be difficult to produce a sample that aligns with the national sample frame <sup>7</sup>	<ul style="list-style-type: none"> <li>To generate information on a community's nutritional status, food environment, attitudes, norms, and values. <b>Example:</b> <a href="#"><u>Food Price Crowdsourcing in Africa (FPCA)</u></a></li> </ul>

\*Citizen-generated data is not inherently open or freely available to everyone

\*\*Open data has served as a catalyst for innovations

# Digitalization



**Description:** Using digital technology to transform systems or processes to bring efficiency to operations and improve service delivery

Sub-categories	Definitions	Application(s) to nutrition
<b>Electronic health records (EHRs)</b>	Systemized collection and digital storage of patient health information during visits with health providers <sup>8</sup>	<ul style="list-style-type: none"> <li>To allow for easy, real-time access to patient-level health and nutrition data due to portability* and interpretability** of EHRs across providers and clinical settings to better inform care. <b>Example:</b> <a href="#">CommCare for Nutrition</a></li> <li>To aggregate records and monitor “real-time” population-level data on status and services. <b>Example:</b> <a href="#">SMART+</a></li> </ul>
<b>Blockchain</b>	A system of creating digital records in a permanent, verifiable, and safe manner across a network of computers. Individual digital records, called blocks, are linked together in a single list, called a chain <sup>5</sup>	<ul style="list-style-type: none"> <li>To safely link digital patient records together across a network of computers to improve data accuracy and access for providers.</li> <li>To improve supply chain management and tracking of food and nutritional products (e.g., RUTFs or biofortified food).</li> </ul>

\*Portability of EHRs means various providers have access to the records even if they work in different clinical settings

\*\*Interpretability of EHRs means the different systems used in clinical settings can read each other’s data even if they are running on different technology



# Geospatial Data & Statistics



**Description:** Tools which utilize geospatial data for geographic mapping and to conduct analysis

Sub-categories	Definitions	Application(s) to nutrition
<b>Remote Sensing</b>	<p>“The process of detecting and monitoring the physical characteristics of an area by measuring its reflected and emitted radiation at a distance (usually through satellite or aircraft). Special cameras collect remotely sensed images, which help researchers ‘sense’ things about the Earth.”<sup>9</sup></p>	<ul style="list-style-type: none"> <li>To collect data on food security using satellites or drones (e.g., by detecting crop production) or to generate predictions when datasets are paired with artificial intelligence.</li> </ul>
<b>Geospatial mapping</b>	<p>The tying of data to a geographic location, often portrayed on a map, using spatial analysis techniques<sup>10</sup></p>	<ul style="list-style-type: none"> <li>To visualize nutrition-related data on a map for ease of use. <b>Example:</b> <a href="#"><u>Hand in Hand Geospatial</u></a></li> </ul>
<b>Geographic information systems (GIS)/spatial statistics</b>	<p>Computer-based tools which store, visualize, analyze, and interpret geographic data. They use specialized, digital software (e.g., ArcGIS and QGIS) to combine maps and datasets about environmental events and socioeconomic/health trends<sup>11</sup></p>	<ul style="list-style-type: none"> <li>To help demonstrate nutritional disparities across regions (e.g., rates of acute malnutrition by area). <b>Example:</b> <a href="#"><u>AReNA’s DHS-GIS Database</u></a></li> <li>To identify spatially-linked risk factors for and determinants of poor nutritional status (e.g., cases of other diseases, scale of adverse events such as flooding, and accessibility of food/health services). <b>Example:</b> <a href="#"><u>Fraym’s machine learning to identify areas with high rates of stunting and wasting</u></a></li> </ul>



# Mobile Solutions



**Description:** The use of mobile and wireless technologies for data entry and storage or to support decision-making (often when paired with other innovations on the backend)

Sub-categories	Definitions	Application(s) to nutrition
<b>Data collection tools</b>	The compilation and storage of qualitative and quantitative information using a mobile device. Mobile data collection can either be done in-person or remotely <sup>12</sup>	<ul style="list-style-type: none"> <li>To replace paper-based nutrition questionnaires and forms (e.g., SMART nutrition/food consumption surveys). <b>Example:</b> <a href="#"><u>INDEXX24 Mobile App</u></a></li> <li>To collect and store data in real-time, improving efficiencies even during emergencies. <b>Example:</b> <a href="#"><u>Mobile Vulnerability Analysis and Mapping</u></a></li> </ul>
<b>Wearable devices</b>	Digital technology incorporated into accessories that individuals wear on their bodies (e.g., smart devices, mobiles, tablets) that can sense and track real-time health data <sup>13</sup>	<ul style="list-style-type: none"> <li>To continuously collect individual diet and exercise data and transfer into other devices (e.g., electronic medical records), allowing providers to track patient-level nutrition data, analyze sudden symptoms, and provide more personalized care. <b>Example:</b> <a href="#"><u>HemaApp</u></a></li> </ul>
<b>Case Management apps</b>	Apps that enable healthcare workers to easily capture, track, and manage patients' medical history and document services	<ul style="list-style-type: none"> <li>To input and track patient-level nutrition data to support service delivery (e.g., child growth monitoring) and aggregate the data for monitoring of population nutritional status at the facility, local, subnational or national level. <b>Example:</b> <a href="#"><u>Scope CODA</u></a></li> </ul>
<b>Diagnostic &amp; clinical decision support apps</b>	Apps that identify a possible health condition based on the evidence input (e.g., patient symptoms or measurements) using intelligent algorithms, machine learning, etc. on the backend	<ul style="list-style-type: none"> <li>To quickly diagnose patients with nutritional conditions (e.g., malnutrition based on anthropometric data inputs), increasing the accuracy/speed of diagnoses and simplifying health providers workflows. <b>Example:</b> <a href="#"><u>Child Growth Monitor</u></a></li> </ul>

# Artificial Intelligence (AI)



**Description:** Development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and language<sup>14</sup>

Sub-categories	Definitions <sup>15,16</sup>	Application(s) to nutrition
<b>Machine learning (ML)</b>	Complex statistical techniques and automated data analysis which enable machines to learn and improve at tasks with experience by using algorithms that iteratively identify patterns in data	<ul style="list-style-type: none"><li>To review large volumes of data and discover trends and patterns that can support clinical decisions (e.g., nutrition diagnostics), generate early warning predictions related to emergencies that can impact population nutrition (e.g., outbreaks, famines), or support targeting of resources to the most vulnerable. <b>Example:</b> <a href="#">Nutrition Early Warning System (NEWS)</a></li></ul>
<b>Deep Learning (DL)</b>	“A subset of machine learning composed of algorithms that permit software to train itself to perform tasks (like speech and image recognition). Inspired by the human brain, deep learning works by exposing multi-layered neural networks to vast amounts of data”	<ul style="list-style-type: none"><li>To find patterns of large nutrition datasets otherwise unrecognizable to humans that can predict or model outcomes. <b>Example:</b> <a href="#">DeepFood</a></li></ul>
<b>Natural language processing (NLP)</b>	“Subfield of AI that aims to bridge the divide between the languages that humans and computers use to operate. By using algorithms that allow machines to identify key words and phrases in natural language corpora (i.e., unstructured written text), AI applications are able to determine the meaning of text.”	<ul style="list-style-type: none"><li>To translate spoken word for health records or food diaries to text for analysis. <b>Example:</b> <a href="#">Speech2Health</a></li></ul>
<b>Computer vision</b>	The processing of large amounts of data from images and signals to identify and classify the data	<ul style="list-style-type: none"><li>To automatically track the nutritional composition of a meal via pictures. <b>Example:</b> <a href="#">Show me what you eat</a></li></ul>



# Modeling & simulation tools



**Description:** Tools which analyze data to help make predictions or guide decision-making based on a specific set of conditions\*

Sub-categories	Definitions	Application(s) to nutrition
<b>Economic optimization modeling</b>	Illustrates the potential value and optimum solution as measured by a specific outcome with respect to cost	<ul style="list-style-type: none"> <li>To help maximize the estimated cost efficiencies of nutrition interventions. <b>Example:</b> <a href="#"><u>Optima Nutrition</u></a></li> </ul>
<b>Health impact modeling</b>	Produces estimates of impact of a product or service on the health of a population or estimates disease burden based on predictive indicators	<ul style="list-style-type: none"> <li>To estimate the impact a specific product or event will have on the health or nutrition of a population to inform evidence-based decision making. <b>Example:</b> <a href="#"><u>Outcome Modelling for Nutrition Impact Tool (OMNI)</u></a></li> <li>To optimize healthcare service flow for nutritional services and/or forecast resource demands (e.g., for RUTFs or fortified foods)</li> </ul>
<b>Policy impact modeling</b>	Produces estimates of impact of a specific policy on the health or other outcomes of a population	<ul style="list-style-type: none"> <li>To evaluate policy options based on different predictors and risk factors for health and nutrition (e.g., food system policies) prior to implementation informing decision making at government level. <b>Example:</b> <a href="#"><u>Micronutrient Action Policy Support (MAPS)</u></a></li> </ul>

\*AI (in particular machine learning) is often a part of modeling/simulation.



# Data visuals



**Description:** Visuals which provide graphical representations of data that helps people see trends, outliers, and patterns. Although data visuals in themselves are often not innovative, they can be innovative when paired with other innovations (e.g., geospatial mapping, artificial intelligence).

Sub-categories*	Definitions <sup>17</sup>	Application(s) to nutrition
<b>Dashboard</b>	A collection of graphs, charts, or other visual representations which are used to organize and display information from multiple data sources into one place	<ul style="list-style-type: none"><li>To show selected actionable indicators for nutrition to facilitate monitoring &amp; evaluation, operations, or management. <b>Example:</b> <a href="#">Food Systems Dashboard</a></li></ul>
<b>Scorecards</b>	A visual report which measures and compares indicators against certain benchmarks	<ul style="list-style-type: none"><li>To compare performance on nutrition indicators across countries, geographies, and regions.</li></ul>
<b>Index</b>	Aggregate several indicators into a simple metric (or composite score) to compare performance or outcome data across different units	<ul style="list-style-type: none"><li>To compare nutrition across many countries and drive action (e.g., presence of components for a favorable environment).</li></ul>
<b>Profile</b>	Provide a snapshot of how a geographic area is doing in a particular sector	<ul style="list-style-type: none"><li>To provide an overview of the nutrition landscape within specific countries to a broad audience of country-level stakeholders.</li></ul>

\*Note data visuals rarely fall into only one of these categories – they often mix goals and features across different typologies

# Data collaboratives & partnerships



**Description:** New mechanisms or networks for bringing together different entities (e.g., research institutions, NGOs, government agencies, private companies) to support one or more aspects of the data value chain

Sub-categories	Definitions	Potential application(s) to nutrition
<b>Data collaboratives</b>	Partnerships between various entities (e.g., private companies, academia, government agencies, NGOs) focused specifically on generating or sharing data to create public value <sup>18</sup>	<ul style="list-style-type: none"> <li>To improve the accessibility of important nutrition data through data sharing (e.g., food purchases and diet behaviors). <b>Example:</b> <a href="#"><u>Open-Global</u></a></li> </ul>
<b>Data partnerships</b>	Various entities (e.g., private companies, academia, government agencies, NGOs) working together in support of innovative data initiatives	<ul style="list-style-type: none"> <li>To generate new solutions to address some of the most enduring obstacles related to the nutrition DVC (e.g., data gaps, quality concerns, standardization). <b>Example:</b> <a href="#"><u>Standing Together for Nutrition</u></a></li> </ul>



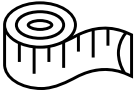

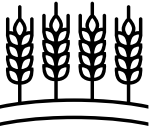
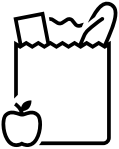
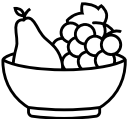
# Key Findings - Nutrition Data Innovations

# Key Finding #1



**There has been a significant number of nutrition data innovations since 2015—we found approximately 60 in the domains and sources we reviewed**

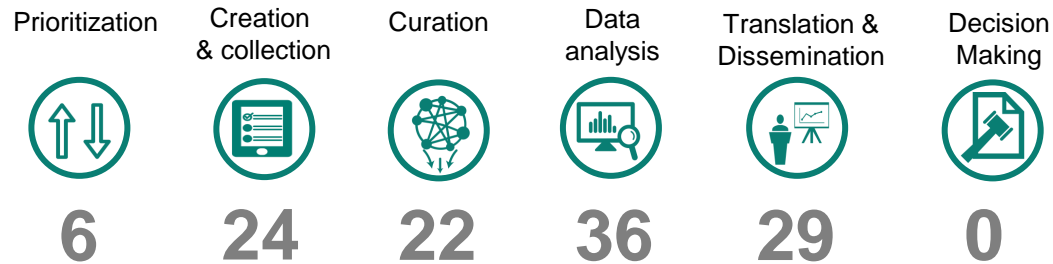
# We found nutrition data innovations across five nutrition domains

<i>Nutrition Domain</i>	<i>Number of Innovations</i>	<i>Examples</i>
 <b>Nutrition Status Data</b>	22	<b>Child Growth Monitor</b> – Mobile app using augmented reality and AI to detect malnutrition using photographs
 <b>Diet Data</b>	21	<b>FAO/WHO Global Individual Food Consumption Tool (GIFT)</b> – Online, open-access repository providing access to harmonized individual quantitative food consumption data
 <b>Food Fortification Data</b>	4	<b>FortifyMIS</b> – Online data collection and aggregation information system for fortification monitoring
 <b>Food Security &amp; Food Environment Data</b>	14	<b>Digital Earth Africa</b> – Provides satellite and earth observation data in an analysis ready format to help address challenges related to food security
 <b>Micronutrient Data</b>	6	<b>Open-Global</b> – An open-access knowledge hub to support the accurate and detailed assessment of nutritional biomarkers from populations globally

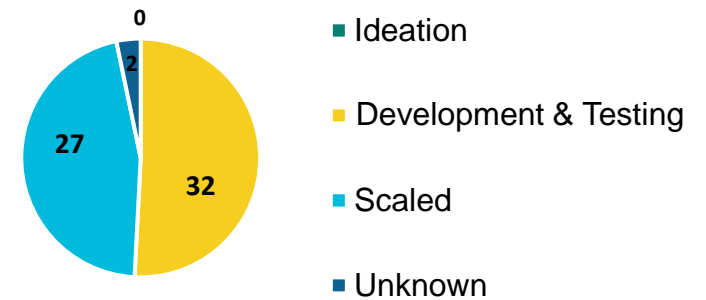


# We broke innovations down into sub-groups by: (1) DVC stage influenced, (2) scaling stage, (3) geography, and (4) top funders

## DVC Stage Influenced\*



## Scaling Stage\*\*



## Geography\*\*



Top countries include Kenya and India

## Top Funders



*The top funders are mostly consistent with top funders for nutrition data and information systems more broadly\*\*\**

\*Please note we mapped the DVC stages to the best of our ability given the limited information on some innovations found

\*\*For details on how we define scaling stages and geography, please refer to Annex 1

\*\*\*For more information on donor funding for ND&IS, please refer to DataDENT's work on tracking donor financing [here](#)

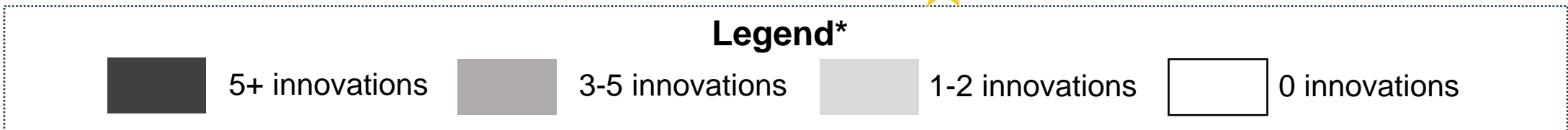
## Key Finding #2



**The majority of nutrition data innovations found are mobile solutions, artificial intelligence, or digitalization**

# The majority of nutrition data innovations fell into the mobile solutions category

	Indicator Development	Digitalization	Citizen-Generated & Open Data	Geospatial Data & Statistics	Mobile Solutions	Artificial Intelligence	Modeling & Simulation Tools	Data Visuals	Data Collaboratives
Nutrition Status		■		■	■	■	■	■	
Diet	■	■	■		■	■	■	■	■
Food Security & Food Environment	■	■	■	■	■	■	■	■	■
Fortification	■	■			■				
Micronutrients				■			■	■	■
<b>Total</b>	<b>6</b>	<b>12</b>	<b>4</b>	<b>7</b>	<b>21</b> ★	<b>12</b>	<b>9</b>	<b>8</b>	<b>6</b>



\*Please note several innovations have been tagged under multiple nutrition domains and/or data innovation categories since data innovations can be used together to generate value across the nutrition data value chain.



# Mobile solutions are leveraged across nutrition domains in a variety of different ways

## Mobile Solutions are used to:

- Collect and store data in **real-time** across several nutrition domains to monitor fortification processes, food security crises, etc.
- Enable **remote data collection** which is critical for capturing nutrition data in emergencies
- Improve the **speed and accuracy of diagnosing nutritional conditions** in the field by using mobile apps to help with complex calculations or diagnose malnutrition from a photo using artificial intelligence algorithms
- Strengthen **community-based child growth monitoring** by using mobile platforms to improve timeliness and accuracy of data
- **Simplify the collection of dietary data** through online food diaries or by automatically calculating nutritional value of food items in photographs using artificial intelligence

*Please note that successful use of mobile solutions is based on affordability and access to cellular devices and in some instances Wi-Fi connection; those without access may be left out of data collection efforts.*

## Examples



### Sanku Smart Dosifier Machine

Technology that collects data from flour mills via cellular-connected dosifiers, granting access to real-time data via GPS & automatic curation into a central, cloud-based dataset

**Scaling Stage:** Scaling

**Geography:** Rwanda, Tanzania, Kenya, & Malawi



### SAM Photo Diagnosis App

Mobile app which uses a photo to automatically diagnose malnutrition in children using geometric morphometric techniques

**Scaling Stage:** Scaling

**Geography:** Senegal

For more examples of mobile solutions being used for nutrition data, please refer to **Annex 2**

**Left Photo:** Project Health Children. Sanku-PHC Wins Product of the Year Awards! Project Healthy Children. Published September 18, 2018.

**Right Photo:** Tasci Z. New app uses a photo to automatically diagnose malnutrition in kids. Creating Hope in Conflict: A Humanitarian Grand Challenge. Published October 16, 2019.

# Artificial intelligence is mainly used to support nutrition status, diet, and food security data

## Artificial Intelligence is used to:

- Provide **predictive insights and forecasting** for malnutrition and food security early warning systems
- Analyze large amounts of data to provide **decision support** around nutrition status based on data collected as well as recommendations around the best nutrition interventions to support based on context
- Improve **accuracy of detecting malnutrition** through analyzing height and weight in photographs of children
- Recognize food items in images to **simplify tracking of food consumption** and provide **personalized nutrition advice** based on foods consumed

*Please note that AI is not always feasible given its implementation requires specialized technical knowledge and equipment which can store and process large amounts of data. Biases may also exist in the AI application (i.e., AI tools recognizing the face of a certain gender or race more often than others).*

## Examples

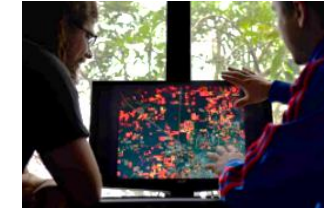


### Hemoglobin Monitor Solution

Device which enables rapid point-of-care hemoglobin testing where a user places their finger on the device and the built-in machine learning algorithms automatically analyze the data to present quick and accurate results

**Scaling Stage:** Pilot

**Geography:** India



### Nutrition Early Warning System (NEWS)

System which uses machine learning to aggregate and analyze satellite imagery & traditional data to provide ongoing surveillance of nutrition threats and options for nutrition interventions

**Scaling Stage:** Pilot

**Geography:** Botswana, Kenya, Malawi, Mali, Nigeria, Rwanda, Senegal, South Sudan, & Zimbabwe

For more examples of artificial intelligence being used for nutrition data, please refer to **Annex 2**

**Left Photo:** Berroth T. Bosch Hemoglobin Monitor: Early detection of anemia without blood tests. Bosch Media Service.

**Right Photo:** Using Big Data and Machine Learning to Power a Nutrition Early Warning SYstem (NEWS) for Africa. CIAT. <https://blog.ciat.cgiar.org/good-news-for-the-fight-against-malnutrition/>

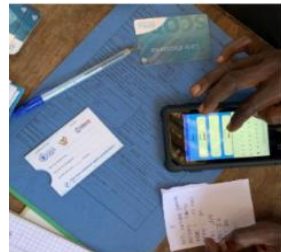
# Digitalization is used to transform data processes for nutrition status, diet, and fortification data

## Digitalization is used to:

- Create **data management platforms which streamline** the process of collecting, storing, analyzing, and sharing nutrition status and diet data
- Automate the process of **collecting and analyzing compliance data to monitor fortified products**
- **Blockchain** can be used to securely trace the entire lifecycle of food products to ensure food safety and credibility\*

*Please note that digitalization may come with risks including data privacy and security as well as the potential of a system failure without proper backup measures which can result in disruptions*

## Examples



**SCOPE CODA**

A cloud-based platform to improve data management in malnutrition treatment programs by giving a digital identity to clients and tracking nutrition services using android devices and a personalized smartcard linked to an electronic database

**Scaling Stage:** Scaling

**Geography:** Afghanistan, The Democratic Republic of the Congo, Madagascar, South Sudan, Tajikistan, Uganda



**SMART+**

An integrated digital infrastructure to improve nutrition assessments which uses nutrition status data from a mobile 3D diagnostic application, analyzes incoming data, aggregates data into a central database, and visualizes results on a public dashboard

**Scaling Stage:** Pilot (expected launch in 2022)

**Geography:** Global

\*Please note no blockchain innovations were included in our review given we have not seen any use cases in the nutrition domains included in our scope.

For more examples of digitalization being used for nutrition data, please refer to **Annex 2**

**Left Photo:** World Food Programme. CODA (Conditional On-Demand Assistance). <https://innovation.wfp.org/project/scope-coda>

**Right Photo:** SMART. SMART+. <https://smartmethodology.org/smartplus/>

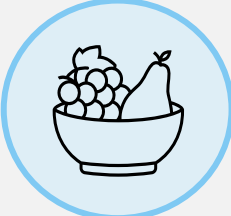
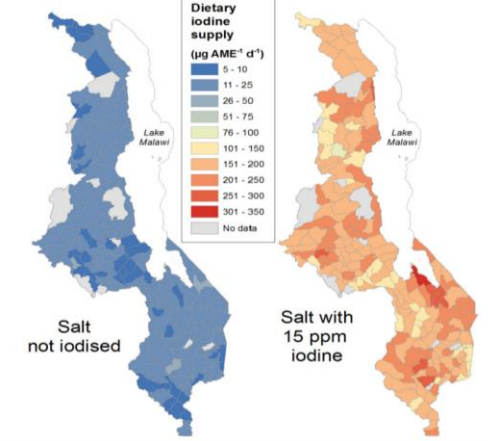
## Key Finding #3



**Nutrition data innovations have started to bring solutions to fundamental data challenges, but there is more work to do given challenges remain**

# Nutrition data innovations are addressing critical challenges across the nutrition data value chain (Selected Example 1/2)


As examples\*:

Nutrition Domain	Example Data Challenges	Innovations to Address Some Challenges
 <p data-bbox="326 982 547 1053"><b>Micronutrient Data</b></p>	<ol style="list-style-type: none"> <li>Overall <b>lack of new data</b> due to high costs and logistical constraints around data collection</li> <li><b>Incomplete &amp; poor-quality data</b> due to lack of standardized protocols to assess micronutrients</li> </ol>	<p><b>Modeling and simulation tools</b> are being used to provide estimates of micronutrient deficiencies where primary data is not available</p> <p><b>For example:</b> Micronutrient Action Policy Support (MAPS) tool - communicate estimates of dietary micronutrient supplies &amp; deficiency risks at national &amp; sub-national scales in Africa</p>  <p data-bbox="1549 1263 2211 1322"><i>Maps show dietary iodine supplies in Malawi with &amp; without iodization of salt</i></p>

\*Please note we did not conduct a comprehensive gap analysis and most of the information presented is based on stakeholder interviews.

Photo Source: Nutrition Modeling Consortium. Micronutrient Action Policy Support. <https://www.nyas.org/media/22192/maps-51520.pdf>

# Nutrition data innovations are addressing critical challenges across the nutrition data value chain (Selected Example 2/2)

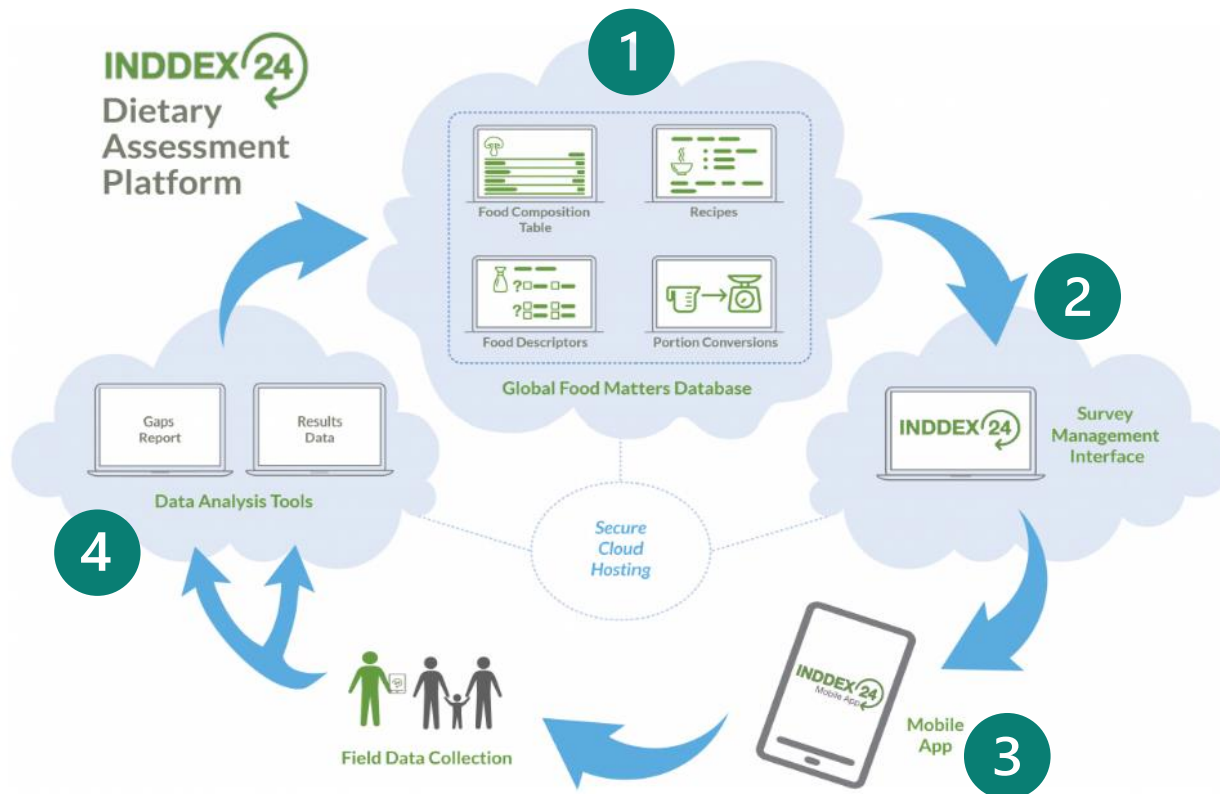
Nutrition Domain	Example Data Challenges	Innovations to Address Some Challenges
 <p data-bbox="341 915 496 943"><b>Diet Data</b></p>	<ol style="list-style-type: none"> <li data-bbox="614 515 1189 591">1. Overall <b>lack of time-relevant data</b> on food consumption</li> <li data-bbox="614 639 1189 833">2. Data collection is <b>expensive &amp; complex</b> given diets change seasonally and current methods require large amounts of data to be collected &amp; stored</li> <li data-bbox="614 882 1189 1005">3. Not much happening around the <b>use and application of data</b> collected for decision making</li> </ol>	<ul style="list-style-type: none"> <li data-bbox="1207 515 2160 591">• <b>Indicator development</b> efforts help to standardize the measurement of different aspects of diet (e.g., diet quality)           <div data-bbox="1251 625 2277 819" style="background-color: #e0f2f1; padding: 5px; margin-top: 5px;"> <p data-bbox="1268 644 2201 801"><b>Ex. Gallup Global Dietary Quality Project</b> - a new partnership to pioneer the global measurement of diet quality by generating data and tools to enable routine, valid, and comparable diet data collection</p> </div> </li> <li data-bbox="1207 839 2237 915">• Innovative tools to <b>measure food consumption</b> are advancing data collection efforts           <div data-bbox="1251 933 2277 1105" style="background-color: #e0f2f1; padding: 5px; margin-top: 5px;"> <p data-bbox="1268 939 2219 1090"><b>Ex. Speech2Health</b> - voice-based mobile nutrition monitoring system that converts spoken food intake data to text and uses AI to search the food in a nutrition database to accurately compute calorie intake values</p> </div> </li> <li data-bbox="1207 1115 2226 1290">• Modeling &amp; simulation tools are used to <b>optimize diets</b> <div data-bbox="1251 1168 2277 1300" style="background-color: #e0f2f1; padding: 5px; margin-top: 5px;"> <p data-bbox="1268 1182 2226 1290"><b>Ex. School Meal Planner Plus</b> - digital solution that optimizes school meals by making them simultaneously more nutritious, cost-efficient, and locally sourced</p> </div> </li> </ul>



# Some innovations are addressing several data challenges at once such as the INDEXX24 Dietary Assessment Platform

Platform which provides researchers with access to tools needed to collect, process, and analyze dietary data.

The platform has 4 main components:



This platform helps to address the following data challenges:

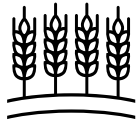
1. **Availability & accuracy of data**—INDEXX24 app allows for flexible, real-time data collection and guides data collectors through a food consumption survey with quick data quality checks to ensure accuracy
2. **Data processing & analysis**—The time and cost of data preparation is made more efficient through the data analysis tools

For more information, please refer [here](#)

Photo Source: Integrated Solutions. <https://index.nutrition.tufts.edu/integrated-solutions>

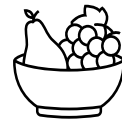
# Additional investments are needed to address remaining data challenges across nutrition data domains

*Some examples include:*



## Fortification

- Methods to determine the **selection of appropriate food vehicles** best suited for each context
- Improved metrics to assess if **those in need are receiving adequate amounts** of a fortified food



## Micronutrients

- **Standardization of protocols** to assess micronutrient intake
- Fast, reliable, and low-cost **diagnostic tools** to collect high-quality data on micronutrient status



## Diet

- Overall need for **more individual-level dietary data**, however high costs and complex methods remain barriers
- **Disaggregated analysis** of dietary data by age and sex to ensure programs target at-risk populations



## Key Finding #4



**Data innovations from other sectors can be leveraged to strengthen nutrition data value chains**

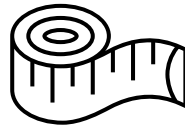
# Geospatial data and statistics innovations are used in the agricultural and health sectors, especially in context of COVID-19, but were not widely found in nutrition

## Benefits of geospatial data & statistics

- Allows for relatively easy, timely, and repetitive data collection over a range of constantly changing areas at a lower cost than terrestrial alternatives
- Visualization of spatial information contextualizes data and allows for the analysis of geographic trends and predictors of health, helping decision-makers plan programs and implement policies
- Useful input for generating predictive analysis using artificial intelligence

*However, its use is not always feasible given some geospatial tools require complex technologies and specialized technical skills, are expensive, and not always easy to integrate into current systems.*

## Promising example in nutrition



*Fraym uses machine learning to weave together primary data, sensing data, and satellite imagery into outputs on population nutrition*

## Examples in agriculture and health



**FAO's Hand-in-Hand Geospatial Data Platform** - build stronger food and agriculture sectors post COVID-19 with rich datasets and interactive tools for evidence-based decisions



**Esri's COVID-19 ArcGIS Hub** - gather and share critical information on the pandemic (e.g., disease spread) for surveillance

**Left Photo:** FAO. FAO launches Hand-in-Hand geospatial data platform to help build stronger food and agriculture sectors post COVID-19. Published July 2020.

<https://www.fao.org/news/story/en/item/1298766/icode/>

**Right Photo:** ESRI. COVID-19 GIS Hub. <https://coronavirus-resources.esri.com/>

# While nutrition has started to leverage the potential of citizen-generated data, more work can be done to build off the current momentum in the broader data innovation space

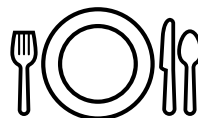
## Benefits of citizen-generated data (CGD)

- Allows for faster, less expensive, and more frequent data collection
- Closes data gaps and improves coverage by collecting information directly from community members, especially individuals commonly missed or excluded in data efforts
- Strengthens the relationship between data users and national statistic offices as well as increases public trust in the data produced

*A few considerations to keep in mind -*

- 1) *Ensure data is of high quality and representative of the population since it is voluntary & often collected through unstructured or untraditional methods*
- 2) *Interoperability may be a challenge since actors may use different indicator definitions*

## Promising example in nutrition



*Citizen-H2D3 shifts diet data collection pathways from researchers to citizens to provide near real-time intelligence of individual daily dietary diversity*

## Global and regional initiatives to leverage citizen-generated data



**Citizen Science for the SDGs**



**Citizen Science & Open Science Community of Practice**



**Citizen Voice and Action (CVA)**

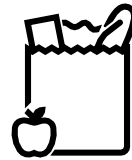
# Similarly, nutrition has started to leverage artificial intelligence, but additional work can be done to harness the technology, especially for predictive analysis

## Benefits of artificial intelligence

- Rapidly collects and analyzes vast amounts of data across multiple sources—at times derived from other innovations (e.g., geospatial data)—improving the effectiveness and efficiency of data processes and decision making
- Generates deeper insights, synthesizes information, and/ or makes conclusions for decision-makers through automation
- Can be leveraged for predictive analysis and forecasting

*Please note AI is not always feasible given its implementation requires specialized technical knowledge and equipment. Biases may also exist in the AI application (i.e., AI tools recognizing the face of a certain gender or race more often than others).*

## Promising example in nutrition



*WFP's Hunger Map LIVE uses machine learning-based predictive modeling to estimate acute food insecurity in near real-time, displayed on a user-friendly, interactive map*

## Use of AI across sectors for meeting the Sustainable Development Goals



*Babylon Health harnesses artificial intelligence to summarize health records, communicate with patients, and interpret combinations of symptoms for diagnoses*



*Alto Analytics and World Economic forum uses pictures of toilets to estimate rates of unsafe sanitation conditions*



*Gro Intelligence combines various datasets paired with machine learning analytics for model building and providing solutions for food and climate related decisions*

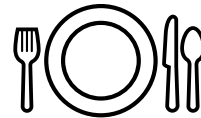
# Data partnerships should continue to be explored to facilitate coordination and collaboration among multiple actors

## Benefits of data collaboratives and partnerships

- Leverages the expertise and collective knowledge of key experts across different organizations to solve the most pressing data gaps (e.g., standardization of high-quality indicators) and other lingering data challenges
- Encourages data sharing and promotes openness across public, private, and academic institutions
- Promotes data governance and stewardship

*Please note the governance of the partnership is critical for expected outcomes. Additionally, lack of funding may mean that the partnership exists but is unable to deliver on its objectives.*

## Promising example in nutrition

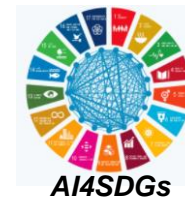


**Gallup Global Dietary Quality Project**, a new partnership between Gallup, Harvard University, and GAIN to pioneer the global measurement of diet quality by generating data and tools to enable routine, valid, and comparable diet data collection

## Examples of key data collaboratives and partnerships for nutrition stakeholders to explore



Global Partnership  
for Sustainable  
Development Data



AI4SDGs



J-PAL's  
Innovations in Data  
and Experiments  
for Action Initiative



## Key Finding #5



**The use of data innovations by nutrition stakeholders has accelerated during the COVID-19 pandemic in response to unique data challenges**

# New and exacerbated data challenges for nutrition due to COVID-19 have catalyzed innovations

## Example Challenges

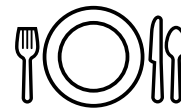
- Barriers to continuous collection of individual and population nutrition data given infection prevention and control procedures
- Minimal existing routine nutrition-sensitive information systems to gather critical data on social protection, food security, and food system resilience
- Lack of up-to-date data on nutrition intervention coverage to target resources due to system disruptions
- Reduced access to timely information for both decision-makers and community members

*Innovations emerged to help address challenges primarily in the following nutrition domains...*



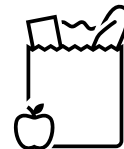
### **Nutrition Status Data**

*malnutrition and intervention coverage*



### **Diet Data**

*Food consumption*



### **Food Security & Food Environment Data**

*Food availability, access, and affordability*

*...And within the following data innovation categories*

Mobile Solutions

Data Visuals

Citizen-generated and open data

Data collaboratives & partnerships

Indicator development

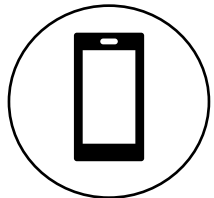


# Data innovations are being used to safely collect critical data and effectively communicate information for decision-making

*As examples:*

## Mobile Vulnerability Analysis and Mapping (mVAM)

*Technology to remotely monitor household food security and nutrition in real-time through collecting data via short mobile phone surveys and live telephone interviews\**



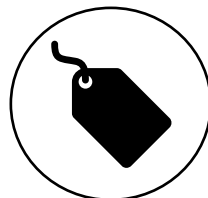
## COVID-19 Monitoring Dashboard

*Dashboard on socioeconomic impacts of COVID-19 on households and individuals based on high-frequency household phone surveys (available for 64 countries)*



## Food Price Crowdsourcing in Africa (FPCA)

*Tool to crowdsource food price information daily directly from citizens, presenting validated data in an open-access dashboard*



## WFP's Global Monitoring of School Meals

*Mapping of school closures to track the number of students missing school meals as a proxy indicator for food insecurity to help decision-makers reach these children*



## Standing together for Nutrition

*A multidisciplinary consortium to assess the impact of COVID-19 on nutritional status, including modeling projected impacts and identifying recommendations*



\*Note the COVID-19 pandemic reignited county government interest in routine food security surveillance systems in particular



# Recommendations

Scaling innovations requires an ecosystem of actors speaking to each other including funders, adopters, end users, and innovators. Our key recommendations are tailored to these groups:

**For innovation adopters:**  
governments and development partners



Identify and prioritize data gaps and challenges and then map to potential solutions—**consider leveraging both existing data sources and methods as well as innovations.**



**Learn from innovations that have been scaled successfully** in other contexts. Also consider tapping into innovations being scaled in the data space more broadly.

**For innovation funders:**



**Take a more strategic approach to investments in innovations** to fill gaps in the nutrition DVC, including consideration of pathways to scale and funding plans.



**Collaborate and coordinate efforts with other stakeholders** with possible co-funding of specific data challenges or types of innovations.



**Identify promising innovations that have successfully scaled across several geographies** to identify critical ingredients needed to scale up innovations.

Equally important is to increase nutrition data innovation awareness and literacy among key stakeholders so they are aware of and understand the tools available and their utility.

# Stakeholders pursuing nutrition data innovations should evaluate feasibility and weigh potential risks



## Feasibility

### Capacity

- ✓ Do **capacities** exist within countries to support and maintain data innovations?
- ✓ Is the data innovation particularly complex and is the **required technical expertise** readily available?

### Cost

- ✓ What are the **costs**?
- ✓ Is **funding** available to cover costs in the short and long term?

### Inputs

- ✓ Are **large quantities of data required** as an input? Are these data readily available?



## Risks

### Existing systems

- ✓ Could adoption or scale up of the innovation **stress existing systems and processes**?

### Data privacy

- ✓ What are the potential risks to **data privacy or security**?

### Data quality & equity

- ✓ Is the data produced of **high quality and representative** of the population?
- ✓ Could the innovations **exclude portions of the population** due to methods used to collect data or underlying bias in backend data used to power innovations?



# Annex 1: Full list of nutrition data innovations

# We assessed the following components of nutrition data innovations

Component	Description
<b>Funder</b>	Funder(s) of the innovation
<b>Nutrition Data Category</b>	Nutrition domain which the innovation is around - nutrition status, diet, food fortification, food environment, food security, or micronutrients
<b>DVC Stage Influenced</b>	DVC stage which the innovation influences - prioritization, creation/collection, curation/access, translation/dissemination, or decision making <i>(see Excel document linked below for more details about each stage)</i>
<b>Scaling Stage</b>	Scaling stage of innovation – <ol style="list-style-type: none"> <li>1. Ideation –idea to address a problem but a prototype has not yet been created</li> <li>2. Development and Testing –a prototype is either being developed or tested in the field to produce evidence to show it could help to solve a specific problem</li> <li>3. Scaling – completed product with sufficient evidence found that demonstrates the product is being successfully utilized and addressing the problem it intended to solve</li> </ol>
<b>Geography</b>	Geography of innovation - <ol style="list-style-type: none"> <li>1. Globally Relevant: Innovations applicable to different countries/contexts</li> <li>2. Country specific: Innovations being researched, developed, piloted, or scaled in a specific country or are country-led and owned</li> </ol> <p><i>*Please note these are not mutually exclusive</i></p>
<b>COVID relevance</b>	Innovations which stemmed from challenges caused by the COVID-19 pandemic
<b>Type of Data Innovation</b>	Type of data innovation used out of the 9 categories (can include multiple)

Please find the full database of nutrition data innovations with a description of each component here.

# Full List of Innovations (1 / 3)

Innovation Name	Description
<a href="#">1,000 Day Nutrient Monitor</a>	At-home diagnostic tool which uses near-infrared spectroscopy so mothers can analyze their own and their baby's nutrient levels, informing proactive diet changes.
<a href="#">Accelerometer as a proxy for an adequate diet</a>	Research study to investigate if an accelerometer in conjunction with food intake data could serve as a new measurement tool for assessing if people are doing more work than they are able to cover for in their diets.
<a href="#">AReNA's DHS-GIS Database</a>	A DHS-GIS database which combines nutrition-relevant information at the individual and household level from the Demographic Health Surveys with a wide variety of geo-referenced data.
<a href="#">AutoAnthro</a>	Digital anthropometry tool which uses 3D imagery and machine learning to capture detailed body parameters, digitize the data, and analyze it.
<a href="#">Changing Access to Nutritious Diets in Africa and South Asia (CANDASA)</a> : New price indexes to measure food system change	Research project which will refine and publish new metrics to measure availability and affordability of foods in markets as well as support countries in implementing these metrics.
<a href="#">Child Growth Monitor</a>	A mobile app to measure and diagnose children for malnutrition by using augmented reality in combination with artificial intelligence to instantly detect malnutrition through a 3D scan.
<a href="#">Citizen-Individual/Household Dietary Diversity Dynamics (Citizen-H2D3)</a>	A front-end tool that engages citizens as providers and consumers of information on diet diversity, and a back-end platform that empowers researchers, institutions, and ultimately individuals to generate evidence-driven and robust insights about the dynamics of diet diversity.
<a href="#">Cockpit</a>	A digital output and outcome monitoring system to provide field staff with timely access to automated, integrated, and visualized data analyses to optimize school feeding programming.
<a href="#">CommCare for Nutrition</a>	Mobile data collection and service delivery platform used to assist with case management, complex anthropometric calculations, and case sharing capabilities to track children through the completion of nutrition programs.
<a href="#">Count Me In</a>	An mHealth app that uses data from users and machine learning processes to make real-time suggestions on feeding techniques and flag cases of potential stunting or wasting using anthropometric measures.
<a href="#">CSDietary Software</a>	A software system developed to support nutrition researchers around the world to enter, manage, and process data from quantitative 24-hour dietary recall surveys.
<a href="#">DeepFood</a>	Research study which aims to improve the accuracy of dietary assessment by analyzing food images captured by mobile devices using deep learning-based food image recognition algorithms.
<a href="#">Develop composite indices of anthropometric data quality</a>	Research project to develop composite indices of anthropometric data quality for use in multi-survey analysis of child health and nutritional status.
<a href="#">Developing metrics to assess advocacy efforts</a>	Research project to derive metrics of effective advocacy that can be applied to a broader set of states and countries.
<a href="#">Dharma Platform</a>	Platform which integrates collection, management, secure storage, analysis, and visualization features to manage projects, staff, identify and collect information, and analyze and share end-to-end data management systems for real time surveillance in crisis affected areas.
<a href="#">Digital Earth Africa</a> (formerly: Africa Regional Data Cube)	Digital platform for accessing and analyzing decades of satellite imagery specific to Africa's land and seas.
<a href="#">Digital Height/Length Measurement Board</a>	A height/length board which uses barcode technology and can automatically transfer data captured onto a phone or computer.
<a href="#">Equitable Strategies to Save Lives (EQUIST)</a>	A web-based analytical platform designed to help decision-makers develop equitable strategies to improve health and nutrition for the most vulnerable children and women.
<a href="#">FAO's big data tool on food chains under the COVID-19 pandemic</a>	An open-access tool which gathers, organizes, and analyzes daily information on the impact of the COVID-19 pandemic on food and agriculture value chains, food prices, food security, and undertaken measures.
<a href="#">Fill the Nutrient Gap (FNG) assessment</a>	A tool that analyses the nutrition situation in a country and identifies the barriers faced by the most vulnerable to accessing and consuming healthy and nutritious foods.
<a href="#">Food Systems Dashboard</a>	Dashboard which covers 230 countries and uses 171 indicators to show national and regional trends in food systems.
<a href="#">FortifyMIS</a>	An online data collection and aggregation approach for fortification monitoring.
<a href="#">Gallup Global Diet Quality Project</a>	An effort to generate both the data and tools to enable routine, valid and comparable diet data collection across countries.
<a href="#">Geospatial Modelling of Changes and Inequality in Nutrition Status amount Children in Mali</a>	Research study which used Demographic and Health Survey data and converted key child, maternal, and household variables into geospatial covariates which were used in a Bayesian geospatial model to provide estimates for stunting and wasting at the subnational level.

# Full List of Innovations (2/3)

Innovation Name	Description
<a href="#">Global Individual Food Consumption Data Tool (GIFT)</a>	A publicly available database that harmonizes information collected through large nationwide and small-scale surveys to provide gender- and age-disaggregated food-based indicators.
<a href="#">Global Open Data for Agriculture and Nutrition (GODAN)</a>	An initiative that seeks to support global efforts to make agricultural and nutritionally relevant data available, accessible, and usable for unrestricted use worldwide.
<a href="#">Hand in Hand Geospatial Platform</a>	A large set of data on food, agriculture, socioeconomics, and natural resources to help strengthen evidence-based decision-making in the food and agriculture sectors.
<a href="#">HemaAPP</a>	An app which uses a smartphone camera to estimate hemoglobin concentrations and screen for anemia.
<a href="#">Hemoglobin Monitor Solution (HMS)</a>	Device which enables rapid point-of-care hemoglobin testing by utilizing built-in machine learning algorithms to analyze data and present quick results.
<a href="#">HungerMap LIVE</a>	A hunger monitoring system leveraging big data and machine learning to display global food security in near real-time, providing vital directions for operations.
<a href="#">iCheck Connect</a>	A companion web and mobile application for an iCheck device which enables wireless transfer of measurement results to your smartphone, tablet or computer and allows for categorization, visualization and interpretation of transferred data.
<a href="#">INDEXX24 Dietary Assessment Platform</a>	Platform which provides unified access to tools researchers in low- and middle-income countries need to assemble and access dietary reference data, conduct timely and effective quantitative food consumption surveys, and analyze results. (Includes the INDEXX24 Mobile App and Global Food Matters Database)
<a href="#">Keenoa</a>	A smart food journal application which allows clients to take pictures of their meal and the nutritional value of the food(s) will be automatically calculated.
<a href="#">Machine-learning approach to identify areas with high rates of stunting and wasting in Chad</a>	Machine-learning based approach to identify areas with high rates of under-5 stunting and wasting in Chad, and map populations who may be among the first impacted by rising food prices and reduced incomes.
<a href="#">Mapping child growth failure (CGF) in Africa between 2000 and 2015</a>	Research study using Bayesian model-based geostatistics, which uses geo-referenced child anthropometry survey data and gridded covariates over space and time, in an ensemble modelling framework to produce estimates of stunting, wasting, and underweight for children under five.
<a href="#">Mbiotisho</a>	A mobile phone application used by individuals to record and track indicators of their own health and nutrition status.
<a href="#">Methods for Extremely Rapid Observation of Nutritional Status (MERON)</a>	A machine learning tool to detect malnutrition through photographs by using a facial recognition and processing algorithm.
<a href="#">Micronutrient Action Policy Support (MAPS)</a>	A web-hosted tool which communicates estimates of dietary micronutrient supplies and deficiency risks at national and sub-national scales in Africa.
<a href="#">Mobile Vulnerability Analysis and Mapping (mVAM)</a>	Mobile technology to remotely monitor household food security and nutrition, and food market-related trends in real-time.
<a href="#">Nutrition Early Warning System (NEWS)</a>	System which processes data relevant to food and nutrition in sub-Saharan Africa to improve nutrition using machine learning.
<a href="#">Nutrition Visualizer</a>	An interactive visualisation framework to illustrate the impact pathways affecting nutrition outcomes.
<a href="#">OMOMI</a>	An mhealth app, web, and SMS service which helps mothers track immunization, monitor growth and development, and manage diarrhea at home.
<a href="#">OpeN-Global</a>	An open-access knowledge hub designed to support the objective, accurate, and detailed assessment of nutritional biomarkers from populations globally.
<a href="#">Optima Nutrition</a>	A quantitative tool which provides practical advice to governments to assist with the allocation of current or projected budgets across nutrition programs.
<a href="#">Outcome Modelling for Nutrition Impact Tool (OMNI)</a>	A tool used to estimate nutrition and non-health impacts due to nutrition interventions and empower decision-makers to maximize future program impact as a result of specific program investment(s).
<a href="#">PalmATrack</a>	An online platform designed to capture live production data to inform about regulatory compliance with fortification standards.

# Full List of Innovations (3/3)

Innovation Name	Description
<a href="#">Partnership between GODAN &amp; University of Nottingham</a>	Partnership to maximize the impact of projects tackling a range of emerging issues across the food system including the geonutrition programme to improve estimates of micronutrient deficiency risks in Ethiopia and South Asia.
<a href="#">Periodic Table of Food Initiative</a>	A public database of the biochemical composition and function of the food we eat.
<a href="#">Prime Diet Quality Score (PDQS)</a>	A diet quality scale composed of 21 food groups that account for both healthy and unhealthy food consumption.
<a href="#">Q-Plex Human Micronutrient Array</a>	A multiplexed immunoassay for use in a laboratory which can measure up to 18 different biomarkers can be measured in one reaction.
<a href="#">RapidPro</a>	An open-source platform of applications that helps governments deliver and collect rapid and vital real-time information and use that data to reach those most in need.
<a href="#">SAM Photo Diagnosis App</a>	An app which can diagnose malnutrition using geometric morphometric techniques and mobile phone technology.
<a href="#">Sanku Smart Dosifier Machine</a>	Technology that collects data from flour mills via cellular-connected dosifiers to add key nutrients, granting access to real-time data on maintenance, machine tracking, nutrient contents and performance via GPS and automatic curation into a central, cloud-based datasets.
<a href="#">School Meal Planner (SMP) Plus</a>	A digital solution that uses databases on food prices and food composition paired with a mathematical algorithm to calculate cost-efficient, nutritious, locally sourced meals.
<a href="#">SCOPE CODA (Conditional On-Demand Assistance)</a>	A cloud-based client management system which gives a digital identity to clients and tracks nutrition and healthcare services.
<a href="#">Show me what you eat: Assessing Diets with Images</a>	Use of real-time smartphone meal pictures to better monitor and assess the quality of diets and provide tailored recommendations to improve them by using machine learning algorithms.
<a href="#">Smart+</a>	An integrated digital infrastructure that combines the use of a mobile 3D diagnostic application for field staff with a synchronized global data dashboard and aggregator for analysts and policy makers.
<a href="#">Soko-Foods</a>	A mobile app that uses AI algorithms to automatically allow the user to track his/her nutritional feeding, access an appropriate nutritional diet, set nutritional goals, and schedule a one-on-one meeting with a nutritional expert.
<a href="#">Speech2Health</a>	A voice-based mobile nutrition monitoring system that devises speech processing, natural language processing (NLP), and text mining techniques in a unified platform to facilitate nutrition monitoring.
<a href="#">Unified Nutrition Information System (UNISE) for Ethiopia</a>	Unified information system designed to provide data on nutrition-sensitive and nutrition-specific indicators.
<a href="#">WHO Anthro Survey Analyser</a>	An online tool used to carry out analyses of anthropometric survey data for children under five years of age based on weight and height measures.



## Annex 2: High level overview of innovations found within each nutrition domain

# Nutrition Status Data Innovations

## Description of Innovations Found

One innovation found around **developing composite indices** of anthropometric data quality.

Examples: [Develop composite indices of anthropometric data quality](#)

**Mobile solutions** include apps to measure and monitor child growth and apps to assist with case management and clinical decision support around child growth, feeding, and anemia. Many mobile solutions use **artificial intelligence** on the backend.

Examples: [CommCare for Nutrition](#); [Count Me In](#); [Dharma Platform](#); [OMOMI](#); [RapidPro](#); [SAM Photo Diagnosis](#); [SCOPE CODA](#); [SMART+](#); [PIXA\(3\)](#); [HemaAPP](#)

**Digitalization** is used to bring efficacy to data processes and management for both anthropometric and general nutrition data.

Examples: [AutoAnthro](#), [CommCare for Nutrition](#), [Digital Height/Length Measurement Board](#), [SCOPE CODA](#), [SMART+](#)

Bayesian **geospatial models** are used to estimate nutrition indicators including stunting and wasting across different geographic areas. Additionally, a database which links nutrition information from the DHS with **geo-referenced data** was created.

Examples: [Geospatial Modelling of Nutrition Status among Children in Mali](#); [Mapping child growth failure in Africa, 2000-2015](#); [AReNA's DHS-GIS Database](#)

**Artificial intelligence** is used for more accurate diagnostics and clinical decision support. Four innovations used machine learning to detect malnutrition using photographs, 1 innovation used AI to determine hemoglobin values to aid in anemia management, and 1 innovation used AI to provide clinical decision support around feeding, growth, and anemia in children.

Examples: [AutoAnthro](#); [Child Growth Monitor](#); [Count Me In](#); [Hemoglobin Monitor Solution](#); [Methods for Extremely Rapid Observation of Nutritional Status \(MERON\)](#); [SMART+](#); [Machine-learning approach to identify areas with high rates of stunting and wasting in Chad](#)

**Data visuals** are used to show nutrition status indicators through dashboards and maps. One visualization shows impact pathways affecting nutrition.

Examples: [EQUIST](#); [Nutrition Visualizer](#); [SMART+](#)

Two other nutrition status data innovations which do not fit into our 9 categories include an information system designed to bring together nutrition sensitive and specific indicators in Ethiopia called the [Unified Nutrition Information System \(UNISE\)](#), and an online tool to carry out analyses of anthropometric survey data called the [WHO Anthro Survey Analyser](#).

No innovations found in the indicator development, citizen generated and open data, and data collaboratives category.

# Diet Data Innovations

## Description of Innovations Found

**Indicator development** includes efforts to improve measurement of diet quality and proxy indicators for adequate food consumption.

Examples: [Gallup Global Diet Quality Project](#); [Prime Diet Quality Score](#); [Study to determine if an accelerometer worn could be a proxy for an adequate diet](#)

**Mobile solutions** include apps to collect individual food consumption data either through a survey or food diary. Some apps use **artificial intelligence** on the backend to determine food items from a picture as well as provide an accurate calculation of the nutritional value of meals and even personalized nutrition advice.

Examples: [Soko-Foods](#); [Citizen-H2D3](#); [Count Me In](#); [INDEXX24 Mobile App](#); [Keenoa](#); [Mbiotisho](#); [Show me what you eat: Assessing diets with images](#); [Speech2Health](#); [DeepFOOD](#)

**Citizen generated data** is used to collect data from large groups to capture information on different aspects of diet including food consumption and dietary diversity as well as around the food environment including food prices, access to markets, etc. **Open data** is used to ensure that researchers and other decision-makers have access to dietary data previously collected.

Examples: [Citizen-H2D3](#); [INDEXX24 Global Food Matter Database](#); [Mbiotisho](#); [Premise App](#); [Show me what you eat: Assessing diets with images](#); [GODAN](#)

**Modeling and simulation tools** are used to optimize nutritious meals through intervention programs.

Examples: [School Meal Planner \(SMP\) Plus](#)

**Digitalization** is used to streamline the process of collecting, storing, analyzing and sharing dietary data.

Example: [INDEXX24 Dietary Assessment Platform](#)

**Data visuals** are used to show trends around food consumption as well as impact pathways affecting diet and nutrition.

Examples: [Nutrition Visualizer](#)

**Data collaboratives and partnerships** are focused on the creation, collation, use, and dissemination of dietary data and metrics.

Examples: [Global Individual Food consumption Tool \(GIFT\)](#); [Gallup Global Diet Quality Project](#); [GODAN \(Global Open Data for Agriculture and Nutrition\)](#); [Periodic Table of Food Initiative](#)

No innovations found in the geospatial data and statistics category.

# Food Security & Food Environment Data Innovations

## Description of Innovations Found

One innovation found around **developing new metrics** to measure the availability and affordability of nutritious foods and food groups in markets.  
Example: [Changing Access to Nutritious Diets in Africa and South Asia \(CANDASA\)](#)

**Citizen generated data** is used in one tool which gathers and analyzes data from tweets and news articles related to the impact of the COVID-19 pandemic on food value chains and food security.  
Example: [FAO Big Data Tool on food chains during COVID-19](#)

**Mobile solutions** are used to collect real-time in food security crises with some solutions used to remotely monitor household food security and nutrition.  
Examples: [Dharma Platform](#); [Mobile Vulnerability Analysis and Mapping \(MVAM\)](#)

**Geospatial tools** are used to collect, organize, analyze, and map agriculture food security data and statistics.  
Examples: [Digital Earth Africa](#); [Hand in Hand Geospatial Platform](#); [Machine-learning approach to identify areas with high rates of stunting and wasting in Chad](#)

**Artificial intelligence** is used to provide predictive insights for malnutrition and food security early warning systems often in combination with **modeling and simulation** tools.  
Examples: [HungerMap LIVE](#); [Nutrition Early Warning System \(NEWS\)](#); [Machine-learning approach to identify areas with high rates of stunting and wasting in Chad](#)

**Modeling and simulation tools** are used to understand costs and affordability of diets.  
Example: [Fill the Nutrient Gap \(FNG\)](#)

**Data visuals** include maps and dashboards which show local, regional, and global trends in food security as well as data on markets, access, and affordability of food.  
Examples: [Hand in Hand Geospatial Platform](#); [HungerMap LIVE](#); [Nutrition Visualizer](#); [Food Systems Dashboard](#);

**Data collaboratives and partnerships** are around promoting open data to fill knowledge gaps around food security.  
Example: [GODAN \(Global Open Data for Agriculture and Nutrition\)](#)

No innovations found in the digitalization category.

# Fortification Data Innovations

## Description of Innovations Found

**Mobile solutions** are used to measure individual vitamins and minerals in foods as well as collecting real-time data to monitor the fortification process.

Examples: iCheck Connect; Sanku Smart Dosifier Machine

**Digitalization** is being used to simplify the process of compliance data collection and monitoring to ensure high quality fortified products and improve program performance.

Examples: FortifyMIS; Sanku Smart Dosifier Machine; iCheck Connect; PalmATrack

No innovations found in the indicator development, citizen generated and open data, modeling and simulation tools, geospatial data and statistics, artificial intelligence, data visualization tools, and data collaboratives categories.



# Micronutrient Data Innovations

## Description of Innovations Found

**Modeling and simulation tools** are used to provide estimates of dietary micronutrient status and deficiency risks.

Example: Micronutrient Action Policy Support (MAPs)

**Data visuals** are used to visually map the burden of micronutrient deficiencies as well show impact pathways affecting nutrition including micronutrient status.

Example: Micronutrient Action Policy Support (MAPs); Nutrition Visualizer

**Data collaboratives and partnerships** are around improving the assessment of nutritional biomarkers globally as well as the estimates of micronutrient deficiency risks. One partnership used **geospatial mapping** of crop and soil samples to identify the nutrient deficiencies in the soil and how this influences nutrition pathways.

Examples: OpeN-Global; Partnership between GODAN & University of Nottingham

One other micronutrient data innovation which does not fit into our 9 categories is the Q-Plex Human Micronutrient Array which is a multiplexed immunoassay that can measure 18 biomarkers in one reaction to ultimately enable effective population surveillance of micronutrient status.

No innovations found in the indicator development, citizen generated and open data, mobile solutions, digitalization, or artificial intelligence categories.



## Annex 3: List of stakeholders consulted

# Stakeholders consulted around both nutrition data innovations and data innovations more broadly

Organization	Person(s) Consulted
Fraym	Krsna Powell
Gates Foundation	Jonathan Gorstein & Shelly Sundberg
GAIN	Mduduzi Mbuya
Independent	Ellen Piwoz
Independent	Muchiri Nyaggah
Johns Hopkins University	Alexandra Bellows & Sweta Manohar
Johns Hopkins University	Nadia Akseer
Micronutrient Forum	Reed Atkin
R4D Innovation Team	Thomas Feeny, Sweta Govani, Meghan Erkel, & Olivia Elson
Sight and Life	Anirudh Poddar & Srujith Lingala
USAID	Omar Dary & Erin Milner
World Food Programme	Nicolas Bidault

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## Annex 4: Key Literature consulted for data innovation categories

# Key literature for definitions of data innovation categories

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