PROJECT BRIEF

Learnings from the Multidimensional Digital Inclusiveness Index: Implications of Data Quality on Evaluations of Digital Inclusiveness

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Front Cover photo: Farmers using digital tools in banana plantation. (*photo:* Media Lens King/Shutterstock)

Back Cover photo: Community harvesting rice in open fields (*photo*: soft light/Shutterstock)

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Contents

Summary

This brief is part of the Multidimensional Digital Inclusiveness Index (MDII) Learnings Series and synthesizes key insights on how Data Quality (DQ) shapes the reliability and interpretability of digital-inclusiveness assessments. The MDII is a scientific evaluation framework to assess how digitally inclusive agrisystem tools are. It has been piloted across FAO- WaPOR-based digital tools to evaluate how different user groups experience accessibility, usability, risks, and broader institutional enablers in real operational environments. These evaluations rely on multi-user evidence from innovators, domain experts, direct users, and downstream beneficiaries.

Findings reveal that gaps in completeness, consistency, and provenance weaken the ability to understand digital inclusiveness outcomes. Missing submissions, uneven reporting across users, and schema misalignments can affect indicator calculations and reduce comparability across tools and contexts. These challenges often reflect institutional realities such as low connectivity, distributed responsibilities, and variable documentation practices rather than limitations of the tools themselves.

To address these constraints, the brief outlines how structured data-quality practices, and the integration of data management principles can strengthen MDII's evidence base. It also identifies lessons on how more robust data-collection processes and enhanced traceability reduce systemic gaps that distort digital-inclusiveness insights.

Learnings from the Multidimensional Digital Inclusiveness Index: Implications of Data Quality on Evaluations of Digital Inclusiveness

Key Messages

- Digital innovations in agriculture and water management depend on high-quality data to reveal who benefits, who is excluded, and how tools perform under real-world constraints. Weak data reduces interpretability and undermines trust in digital solutions.

- Issues such as missing information, inconsistent records or fragmented data environments make it difficult to assess usability, accessibility, and impact across diverse user groups. These failures limit meaningful comparison across tools and contexts.

- Applying structured quality controls and recognised data-integrity principles helps generate support better development actions for digital tools that work for a wider range of users.

Introduction

Digital inclusiveness has become central to determining whether agricultural and water-management digital tools can achieve meaningful adoption, remain interpretable, and support sustained use, especially in settings characterised by limited connectivity and constrained resources (Heeks, 2017). Even with growing investment in data-driven solutions, many tools barriers still exist in accessibility, trust and risks, which restrict their effectiveness.

The Multidimensional Digital Inclusiveness Index (MDII) was designed as a systematic framework for evaluating how inclusive digital agrisystem tools are for underrepresented groups, such as women, youth, rural communities and the elderly (Opola et al., 2025). It assesses performance across seven linked dimensions spanning accessibility, usage efficacy, beneficial impact, risks and harms, supportive ecosystem, ethical and responsible innovation, and co-creation and governance, with a strong focus on how different user groups interact with digital systems in practice (Martins et al., 2024).

Across IWMI, the MDII has been implemented through WaPOR-based pilot assessments of digital tools supporting irrigation performance analysis, crop monitoring, and agricultural decision-making. These pilots consolidate inputs from innovators, domain experts, direct users, and downstream beneficiaries to create a comprehensive diagnostic view of digital inclusiveness.

The MDII Framework and Data Requirements

The MDII is a scientific assessment system that relies on rigorous data foundations to evaluate the inclusiveness of digital innovations in agrifood systems (Opola et al., 2025; Martins et al., 2024). While its conceptual purpose is to determine whether digital tools are technically sound, equitable, and usable across diverse socio-technical settings, the framework functions in practice as a data-intensive evaluation model that depends on high standards of Data Quality (DQ), assurance, and control.

The organization of the MDII's framework is done through three higher-level domains, or megagroups: Innovation Usage, Social Consequences, and Stakeholder Relationships. These megagroups encompass 7 dimensions, 27 subdimensions, and 90 indicators (see Figure 1).

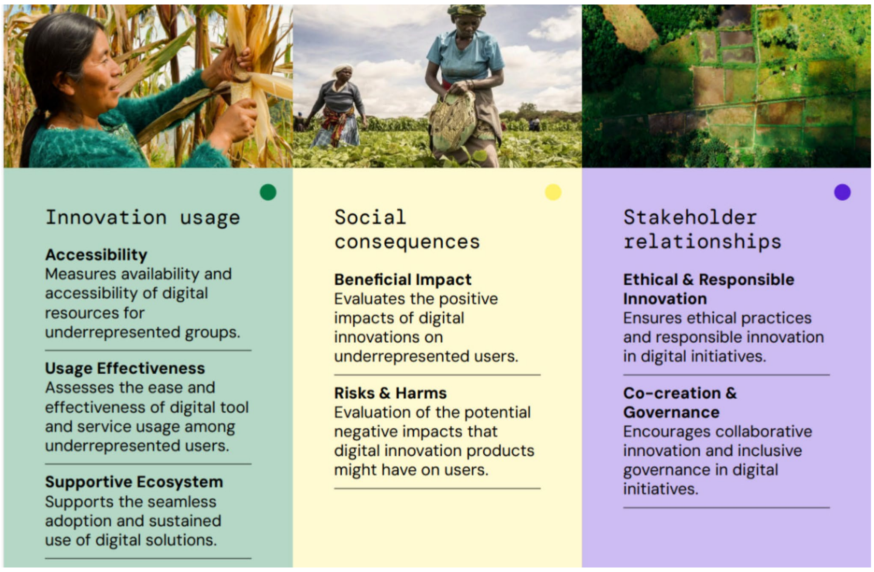

Figure 1. Mega-groups and dimensions of MDII analysis. (*Source*: author' creation)

A central contribution of MDII is the establishment of a consistent, quality-controlled approach to data collection and evidence generation. The framework defines explicit data requirements for each indicator and survey instrument, clarifies the expected structure and completeness of multi-user submissions, and ensures that comparable datasets can be produced across tools, countries, and user groups. By formalising these requirements, MDII strengthens the empirical basis for evaluation and reduces noise, variability, and interpretive ambiguity. This is essential for producing robust diagnostic insights and maintaining reliability across repeated applications.

The framework also supports policy and strategy integration through its emphasis on controlled data processes. Stakeholder-informed recommendations are only credible when they arise from validated, well-governed data. To this end, MDII incorporates established principles of responsible data practices and its architecture is designed to safeguard the provenance and traceability, and minimise errors of collected evidence. Through modular components, the framework ensures that data integrity can be maintained even in low-connectivity environments, which is an operational requirement for evaluations in many agrifood contexts.

User Type Data

The evaluation process relies on a structured, survey-based data collection approach that integrates perspectives from multiple user types involved in the design and use of digital tools. Currently, MDII relies on Kobo ToolBox as its main data collection platform due to it's online and offline capabilities. Evaluations are initiated by innovators or developers, who register the tool and provide the foundational evidence required to establish the evaluation baseline. MDII coordinators then distribute online forms tailored to each user type, gathering submissions from direct users, downstream beneficiaries (when applicable) and domain experts who assess the scientific and operational validity of the tool. The resulting dataset forms the basis of the scoring process and supports the generation of diagnostic insights and targeted recommendations, which are compiled into a final evaluation report.

Figure 2 summarises the four primary user types and the unique perspective each contributes to the assessment. Innovators provide information on system architecture and design intent. Domain experts can as independent third-party evaluators in 6 domains (Gender Equity and Social Inclusion, Data, Information and Communication Technologies, Economics, Human-Centered Design and Country Expertise). Direct users report on usability, interpretability, impacts under real conditions, and how included they were in the development process. Indirect users or downstream beneficiaries describe how the tool's information affects their decisions and highlight inclusion risks and communication gaps.

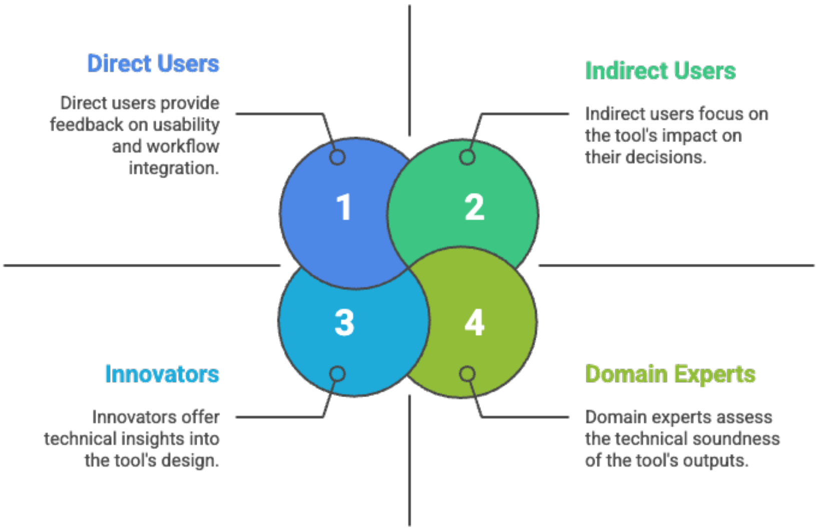

Figure 2. Considered User Types under the MDII evaluation framework. (*Source:* author's creation)

Each user type contributes a distinct form of evidence that supports a multidimensional understanding of digital inclusiveness. Their combined inputs ensure that the evaluation captures performance, user experience and impact in an integrated manner.

Table 1. MDII user typology: roles, evidence, and functions

User Type	Primary Role in the Digital Tool Ecosystem	Type of Evidence Contributed to MDII	Function Within the MDII Evaluation
Innovators	Conceive, design, develop, and maintain the digital tool, including its architecture, assumptions, data flows, and technical choices.	Technical documentation, system descriptions, methodological assumptions, explanations of constraints, and implementation decisions.	Define the technical and design baseline of the tool, enabling evaluators to understand intended functionality, scope, and limitations.
Domain Experts	Independent subject matter specialists who assess the tool from a disciplinary and contextual perspective, without being involved in its development.	Judgments on indicator relevance, methodological soundness, data adequacy, contextual validity, and potential risks of exclusion.	Validate the credibility of the tool's logic and outputs, and identify risks, blind spots, or assumptions that may affect accuracy or inclusiveness.
Direct Users	Individuals who interact directly with the tool. These can include farmers, extension workers, irrigation managers, analysts, and government technicians.	Evidence on use, interpretability, experienced benefits, perceived risks of exclusion or misuse, and the extent to which feedback is incorporated into tool design.	Assess real world usability, experienced beneficial impact, inclusion related risks, and the effectiveness of co creation and feedback mechanisms in supporting equitable use.
Downstream Beneficiaries	Are affected by the information generated by the tool rather than its interface. Include farmers, community groups, and institutional decision makers.	Perceptions of trust, relevance, clarity of communicated outputs, fit with local practices, and social or institutional implications.	Highlight inclusion risks, communication gaps, and unintended effects of the tool's outputs on decision making and equitable access to information.

The assessments highlight where tools perform strongly, where user-facing constraints reduce interpretability or usability, and where specific groups remain at risk of exclusion. This empirical insight reinforces the importance of DQ and user engagement as foundational elements for achieving meaningful inclusiveness. High-quality data enables users to interpret information correctly and to integrate it into routine decision-making. Conversely, shortcomings in DQ reduce trust and can undermine the effectiveness of digital initiatives (Meyer et al., 2020).

MDII Scoring Engine Data Processing

As depicted in Figure 3, each digital tool evaluated through the MDII is scored across three analytical levels: indicators at the micro level, subdimensions at the meso level, and dimensions at the macro level. Indicator-level inputs collected from all user types are aggregated to derive subdimension scores, which are subsequently averaged to produce dimension-level results. All aggregation uses equal weighting across indicators, subdimensions, and contributing user groups to ensure transparency and reproducibility across heterogeneous evaluation contexts.

Figure 3. Macro-, meso-, and micro-levels of MDII scoring. (*Source*: author’s creation)

For each single evaluation cycle, the developed data pipeline embeds DQ by design across all of stages of data lifecycle (see figure 4). The pipeline is implemented using a hybrid relational-dimensional data model:

- **Relational Core:** Raw submissions, user types, tools, indicators, subdimensions, and dimensions are stored as normalized relational entities, with explicit relationships governed by keys such as tool ID, user type, indicator ID, and evaluation cycle. This structure supports the requirements of data integrity, traceability, validation, and provenance control.
- **Dimensional Layer:** Scoring outputs are hierarchically organized across indicator (micro), subdimension (meso), and dimension (macro) levels. Aggregation tables function similarly to a star schema, where indicator and subdimension scores act as facts and contextual attributes.

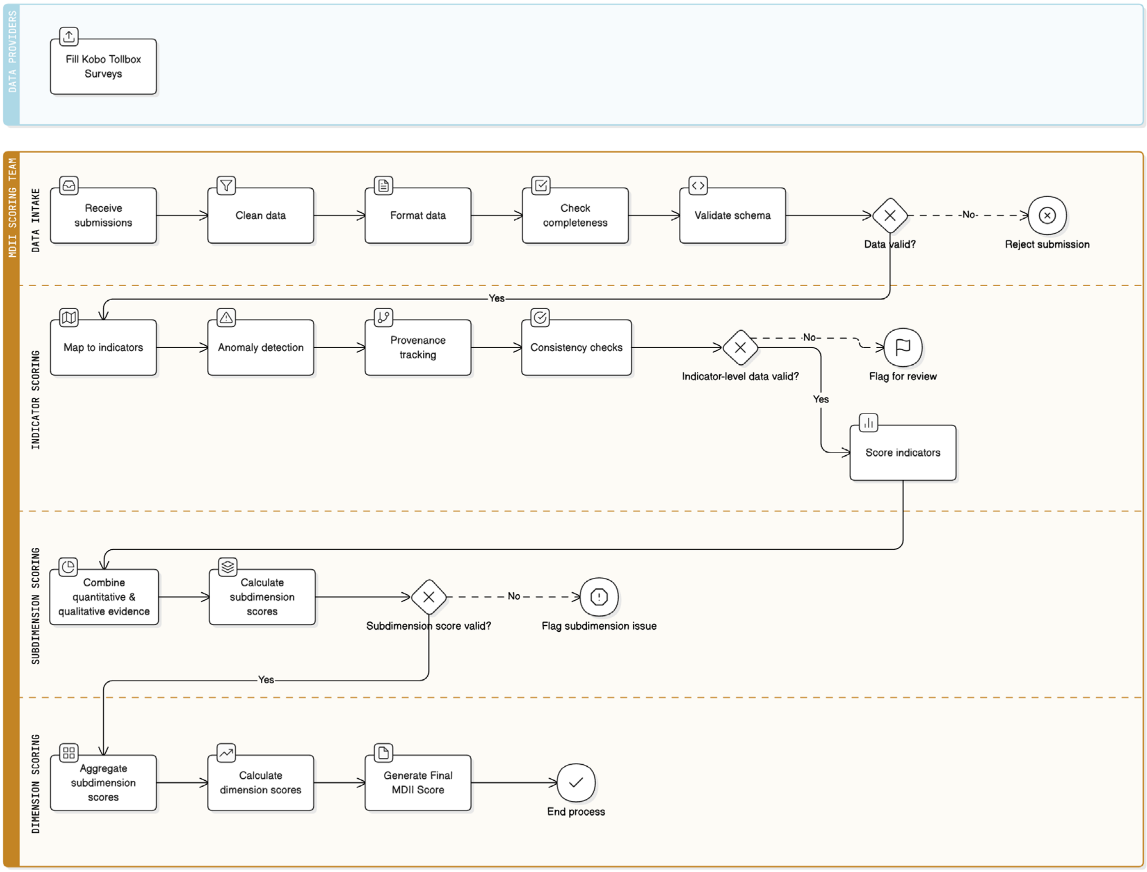

Figure 4. MDII scoring and DQ processing workflow. (*Source*: author's creation)

While useful for overview and comparison, DQ mechanisms operate primarily at the indicator and subdimension levels, where controls such as anomaly detection, provenance tracking, and consistency checks are applied. In this configuration, MDII functions both as an assessment framework and as a structured DQ system.

Dimensions of DQ and their Role in Digital Inclusiveness Confidence

High-quality data is fundamental to the credibility of MDII results. Each MDII score reflects the interpretation of evidence provided. If the underlying data is inaccurate, incomplete or inconsistent, confidence in the final inclusiveness profile decreases and diagnostic precision weakens. DQ control therefore plays a central role in maintaining the reliability of scoring.

According to Guillen-Aguinaga et al. (2025), the following DQ dimensions determine whether the information used supports trustworthy decision-making. Table 2 presents the main dimensions in DQ and what are their implications on MDII results.

Table 2. Main DQ dimensions and their implication on MDII results.

Dimension	Definition and implication on MDII results
Accuracy	Correctness of values relative to real-world truth; poor accuracy affects MDII interpretation because incorrect inputs distort scoring ranges and weaken diagnostic confidence.
Completeness	Presence of required values or records; missing responses reduce the strength of MDII findings and introduce uncertainty in dimension profiles.
Consistency	Agreement across records or respondent types; inconsistencies can obscure true usability barriers or risk patterns detected by MDII.
Timeliness	Data currency and latency; outdated submissions reduce the relevance of scoring, especially when tools evolve rapidly or user groups shift.
Validy	Adherence to formats, ranges, and schemas; conformant data ensures that the MDII scoring engine correctly maps responses to indicators.
Relevance	Structural and referential soundness; compromised integrity affects aggregation steps and can misrepresent the relationship between subdimensions.
Uniqueness	Absence of duplicates that distort counts and skew subdimension averages.

Systemic Implications of Low DQ

Weak DQ introduces systemic failures that undermine the reliability of MDII outputs. These failures propagate through the scoring pipeline, destabilising calculations and distorting subdimension patterns. As noted by Zou et al. (2025) and Chhipi-Shrestha et al. (2023), low completeness increases uncertainty and limits the interpretability and comparability of evaluation results. Three systemic failure modes are particularly relevant to MDII (Aravindhan, 2025; Oleghe, 2020; Bhatia et al, 2023).

The first concerns data noise, which includes inaccuracies introduced during capture, transmission, or recording. Noise often results from human error, misinterpreted prompts, formatting inconsistencies, or interface constraints (Oleghe, 2020). Within MDII, these distortions perturb indicator-level scoring and introduce variance unrelated to real user experience. When noise accumulates across user types, it biases subdimension averages and weakens the clarity of diagnostic patterns.

Secondly, data fog is another concern. It refers to temporal and interpretive ambiguity arising when heterogeneous inputs are difficult to reconcile (Bhatia et al, 2023). For example, differences in response timing, uneven participation rates across user types or unclear mappings between survey items and indicators reduce coherence during processing. Fog delays score generation and can limit MDII's ability to represent the environment of a tool, thereby increasing uncertainty in the digital inclusiveness profile.

Thirdly, the final failure mode relevant for MDII are data islands. These islands emerge when information is fragmented across incompatible systems (Aravindhan, 2025). For MDII, this failure mode could occur when raw submissions, metadata structures,and indicator tables are misaligned or lack shared standards. As fragmentation produces incomplete indicator inputs, inconsistent subdimension scoring and reduced comparability across tools might appear.

Considering these systemic failures in advance, it becomes possible to enhace MDII's capacity to confirm whether observed strengths and weaknesses reflect the tool's real-world performance or merely gaps in reporting.

Current Data Artefacts in MDII and DQ

The MDII scoring pipeline depends on a defined set of data artefacts that constrain how evidence moves from collection to computation. Each artefact has specific role in ensuring that scores across all levels are produced with analytical integrity. The figure 5 below summarises the primary artefacts used throughout the MDII workflow and their corresponding functions.

Figure 5. MDII data artefacts. (*Source*: author's creation)

Beyond the execution of individual evaluation cycles with strict DQ control, there is also an iterative DQ lifecycle to keep on increasing how evidence is standardised, documented, and iteratively improved across assessments. Figure 6 presents an overview of the DQ lifecycle activities. Regular planning activities keep on defining the informational architecture of the evaluation, reference tables, and metadata schemas. Additionally, DQ leverages on Kobo Toolbox's embedded features such as in-form validation, skip logic, and submission logs. The goal is to ensure initial inputs meet minimum structural and provenance requirements before ingestion into Azure's cloud platform for storage.

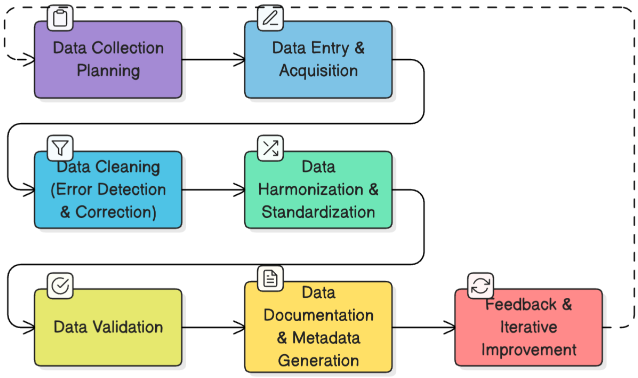

Figure 6. DQ lifecycle and iterative improvement across MDII evaluation cycles. (*Source*: author's creation)

During cleaning, automated routines detect missing fields, type violations, malformed records, and inconsistent scales. These routines apply normalisation procedures that include reverse-coding, harmonisation of Likert categories, and removal of duplicates. Harmonisation and standardisation then align multi-user answers through mapping dictionaries that translate raw question codes into indicator structures, enabling consistent integration across innovators, domain experts, direct users, and indirect beneficiaries.

Validation operates as a gatekeeping stage that enforces schema conformance, verifies user-level completeness thresholds, reconciles metadata descriptors, and flags anomalous patterns that could compromise scoring stability. Documentation and metadata generation ensure that all datasets retain transparent lineage through timestamped logs, versioned scoring outputs, and a storage architecture that clearly separates raw, processed, and consolidated layers.

Finally, iterative improvement closes the loop. Error logs, anomaly patterns, and completeness gaps inform the refinement of survey instruments, mapping files, and scoring scripts. This cyclical mechanism strengthens methodological reliability across successive MDII evaluations and enhances the framework's capacity to operate under diverse field and connectivity conditions.

The FAIR and ALCOA+ Principles

The FAIR and ALCOA+ are well-known international guiding principles that provide a structured lens for assessing DQ. While FAIR emphasises the outward-facing qualities that enable reuse and integration, ALCOA+ reinforces the inward-facing controls for the reliability of the information.

Specifically, FAIR Principles reframe DQ as both (i) an informational and (ii) an infrastructural property that specifies datasets must be findable, accessible, interoperable, and reusable (Guillen-Aguinaga et al, 2025). These requirements clarify how data artefacts must be curated so that evidence can be located, retrieved, integrated, and applied across evaluation cycles without ambiguity. Applying FAIR principles within MDII, ensures that data outputs and supporting artefacts are suitable for future analyses and benchmarking across agrisystems.

Complementing FAIR's external perspective, ALCOA+ provides an internal operational lens on data qualit. By defining the conditions under which data can be considered trustworthy at the point of capture and processing, ALCOA+ specifies that records must be attributable, legible, contemporaneous, original, accurate, complete, consistent, enduring, and available (Miller et al, 2025).

When developing MDII, these elements have been considered by design and across data artefacts, therefore enabling clear lineage tracking throughout the scoring pipeline. Table 3 presents how the current data components relate with FAIR/ALCOA+ principles.

Table 3. Alignment between data artefacts and FAIR/ALCOA+ principles.

Components	Existing Data Artefacts	FAIR/ALCOA+ Alignment
Existence of Formal Data Artefacts and Pipelines	Reference tables, mapping dictionaries, metadata schemas, scored datasets, consolidation pipelines, logs	Ensures data are organised, interoperable, and reliably traceable, strengthening interpretability and long-term confidence in the scoring process.
User Type Data Sources	Innovators, Domain experts, Direct users, Indirect beneficiaries.	Strengthens the robustness of diagnostic patterns by ensuring diverse user perspectives are consistently captured, compared, and triangulated.
Mapping Files and Indicator Construction	Mapping files that convert survey questions to indicators, deterministic score calculation scripts, controlled pipelines for aggregation.	Guarantees consistent and reproducible scoring by enforcing clear variable mappings, validated schemas, and controlled transformations.
Provenance and Submission Logs	Submission timestamps, respondent identity (user type), form versions, metadata logs.	Maintains transparent, auditable evidence flows that allow evaluators to verify when, how, and by whom data were generated.
Consolidation Workflow	Validated copies of scored datasets, metadata consolidation, historical accumulation of scores, anomaly and error logs.	Preserves long-term reliability through validated copies, structured versioning, and stable historical records that support repeatable analyses.
Automated Quality Controls	Automatic detection of missing columns, schema validation, cleaned transformations, standardisation of Likert scales, reverse-coded items, controlled data types.	Reduces ambiguity and analytical noise by enforcing coherent schemas, standardised formats, and systematic validation before scoring.
Storage Architecture for Data Artefacts	Raw input data, processed/scored datasets, consolidated datasets, reference datasets, comment logs.	Supports reliable access and reuse by maintaining structured, well-separated data layers that make retrieval, interpretation, and comparison straightforward.

Pilot Studies

The MDII was first operationalised through pilot evaluations of 8 WaPOR-based digital tools developed by IWMI. Table 4 briefly describes each tool. These pilots offered a structured environment to examine how the framework performs when applied to tools that depend country-specific contexts. The pilots demonstrated both the analytical value of MDII and the conditions under which data can support cross-country comparison, diagnostic interpretation, and actionable refinement.

Table 4. MDII evaluated WaPOR-based tools developed at IWMI.

Theme	Tool	MDII Tool ID	Country	Tool Description
Crop Insurance	Area Yield Index Insurance (AYII)	WP_T02	Ethiopia	AYII is an index-insurance tool that uses high-resolution WaPOR data to estimate yields and trigger payouts, reducing the need for crop-cutting experiments and supporting quicker risk management (Tadesse et al, 2025a).

Irrigation Performance	Irrigation Management Information System of Ethiopia (IMISET)	WP_T01	Ethiopia	IMISET is an irrigation-performance tool that uses WaPOR data to analyse water use and efficiency across Ethiopia's irrigation schemes (Tadesse et al, 2025b).
Water Productivity Monitoring	Wheat Water Productivity Tool (WWPT)	WP_T03	Ethiopia	WWPT is a monitoring tool that uses WaPOR data to assess wheat water productivity across Ethiopia. It provides actionable insights that help extension services and farmers improve water management and crop performance (Tadesse et al, 2025c).
Irrigation Performance	Irrigation Performance Assessment and Diagnostics Tool (IPADT)	WP_T05	Jordan	IPAT Jordan uses WaPOR data to evaluate irrigation performance and crop water use. It supports clearer, more efficient decision-making for water management (Amdar et al, 2025).
Drought Monitoring	PakDMS	WP_T09	Pakistan	PakDMS is a drought-monitoring tool that uses high-resolution WaPOR and environmental data to generate dynamic drought visualizations (Cheema et al, 2025).
Irrigation Performance	Irrigation Performance Assessment Tool (IPAT)	WP_T04	Mozambique	IPAT applies WaPOR data to identify irrigation underperformance and provides automated indicators that guide more efficient water management (Matheswaran et al, 2025).
Irrigation Scheduling Advice	Irrigation Reference to Enhance Yield Smart Irrigation Application (IREY app)	WP_T06	Tunisia	IREY Tunisia applies WaPOR data to generate real-time crop water-demand alerts and support more precise irrigation decisions (Belhaj Fraj et al, 2025a)
Water Demand and Use	Water Use Tool (WUT)	WP_T07	Tunisia	WUT is a water-use monitoring tool that applies WaPOR data to track seasonal irrigation consumption and provide clear insights for managing scarce water resources (Belhaj Fraj et al, 2025b).

Findings and Discussion

Consistent patterns of incomplete and uncertain data emerged across the pilot assessments. Comparing inputs across user groups and regions strengthened the MDII methodology by revealing how reporting practices, documentation quality, and monitoring structures shape the visibility of digital adoption. However, limitations in data completeness and interpretability affected tool-level diagnosis in distinct ways.

Across user types, four recurrent patterns constrained interpretation:

1. **Innovators** – Missing inputs reduce clarity on data provenance, update cycles and governance.
2. **Domain Experts** – Limited responses weaken checks on whether indicators and assumptions reflect local conditions.
3. **Direct Users** – Absent data obscures how tools function under routine workloads, peak demand or low-connectivity environments.
4. **Indirect Beneficiaries** – Missing perspectives limit understanding of distributional effects and how outputs are interpreted downstream.

These gaps are primarily associated with structural constraints such as uneven staffing, offline workflows, and variable connectivity rather than lack of interest or engagement.

Because MDII depends on triangulated evidence, incomplete submissions reduce confidence in final scores and make it harder to distinguish genuine performance issues from limitations in reporting.

For example, as seen in figure 7, explicit uncertainty expressed by domain experts can be observed across tools and MDII dimensions. In the assessment process, this uncertainty is captured through responses marked as *"Don't know"*. These responses arise when evaluators judge that the available evidence is insufficient to support a confident assessment of a given indicator. In practice, "*Don't know*" responses emerge through the absence of supporting documentation. In such cases, domain experts are intentionally not prompted to infer, approximate, or speculate. Instead, MDII preserves the explicit expression of uncertainty as a valid data state and avoiding forced or speculative scoring when evidence is insufficient.

Data shows that distinct patterns of uncertainty emerge across dimensions. Accessibility and Risks and Harms dimensions exhibit consistently higher proportions of "Don't know" responses across several tools, indicating that evaluators often lack adequate visibility into infrastructure constraints, downstream risk exposure, or operational conditions. These dimensions typically depend on context-specific or field-level information that is not always captured in technical documentation or system descriptions. In contrast, dimensions such as Co-creation and Governance and Supportive Ecosystem show lower uncertainty levels across most tools. These areas are more readily assessed through institutional records, partnership structures, and formal governance artefacts, suggesting stronger evidence availability and clearer data lineage. From a data quality perspective, these patterns align most closely with completeness, interpretability, and lineage dimensions.

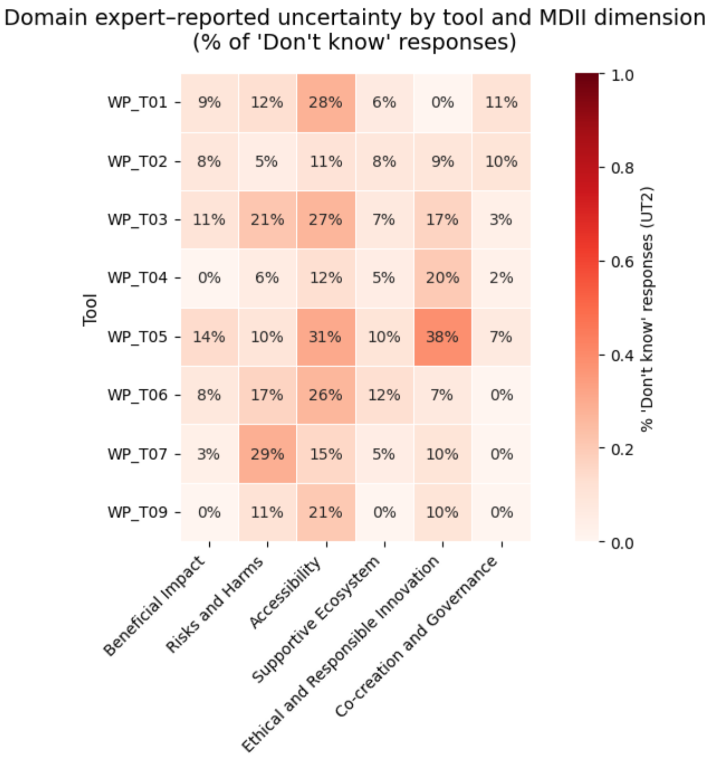

Figure 7. Heatmap findings of domain expert-reported uncertainty. (*Source*: author's creation)

Finally, Table 5 presents the main challenges that were encountered throughout the evaluations and presentes possible solutions, as next steps for increasing data completeness.

Table 5. Common challenges in MDII data collection

Challenge	Description of the challenge	Possible solutions
Differences in how respondents interpret MDII concepts	Respondents interpret items through different lenses, creating inconsistent inputs across subdimensions.	Clearer instructions and short examples reduce variation and improve comparability of responses across user types.
Workload constraints and respondent fatigue	Respondents often complete MDII surveys during peak operational periods, leading to skipped items or minimal responses.	Shorter formats and flexible submission windows substantially increase completion and DQ.
Limited orientation on MDII structure and expectations	Many respondents lack prior exposure to MDII, resulting in incomplete or misaligned answers.	Brief orientation sessions could improve the accuracy and completeness of submissions.
Connectivity and infrastructure barriers	Unstable connectivity interrupts online survey completion.	Offline templates and lightweight formats help reduce data loss and improve reliability.
Value of short qualitative notes	Missing qualitative notes limit interpretation of numerical scores.	Optional one-line comment prompts linked to low or extreme scores encourage contextual explanation.

Lessons Learned

Lessons learned from the MDII pilots highlight the operational conditions that most strongly influence data completeness, consistency, and interpretability across diverse agrisystem contexts. These insights emerge from recurring patterns observed during multi-country evaluations and point to practical mechanisms that strengthen data reliability, streamline collaboration, and support more inclusive and stable evidence generation.

1. Use low-bandwidth and offline alternatives to ensure continuity in low-connectivity environments

Connectivity limitations reduce completion rates and contribute to partial datasets. Offline-enabled forms, downloadable templates, and asynchronous upload options help stabilize data flows in remote areas. These approaches reduce reliance on real-time connectivity and increase the likelihood of complete submissions in dispersed or low-infrastructure settings.

2. Establish clear reporting responsibilities across teams and institutions

DQ suffers when multiple individuals assume that someone else is responsible for specific entries or verification. Defining clear roles for data entry, validation, and review reduces duplication, prevents omissions, and improves the overall coherence of the dataset. Responsibility matrices or simple role charts have proven effective in multi-institutional environments.

3. Build iterative verification and feedback loops into routine workflows

Routine micro-checks, conducted weekly or monthly, help teams identify emerging errors early. When feedback is shared with data collectors in real time, accuracy improves over subsequent rounds. These loops also help projects detect systematic challenges, such as persistent misunderstandings of a question or recurring missing fields.

4. Maintain version-controlled documentation and clear data dictionaries

Consistent definitions and stable metadata structures are essential for longitudinal and multi-location research. Data dictionaries that specify variable definitions, allowable ranges, units, and update histories support coherent analysis across teams. Version control reduces confusion arising from indicator changes or updates introduced mid-cycle.

5. Identify context-specific constraints before data collection begins

Early consultations with field teams, institutions, or community partners help identify barriers such as seasonal workloads, language gaps, gendered constraints on participation, or technological limitations. Understanding these factors upfront allows the design of data collection plans that minimize gaps and reflect local realities more accurately.

Automated reporting strengthens MDII as a data-driven improvement system. By standardizing outputs, accelerating analysis and linking scores to validated recommendations, it shortens the path from evidence to action. This enables faster, more inclusive iteration cycles and supports water- and agriculture-focused institutions in deploying digital tools that deliver clearer value and measurable impact.

Conclusion

High-quality, well-governed data is essential for credible digital inclusiveness assessment. The MDII pilots demonstrate that gaps in completeness, structure, and provenance do not simply reduce analytical precision but reveal deeper institutional and operational constraints shaping how digital tools function across agrisystems. Strengthening data practices therefore enhances both the reliability of inclusiveness scores and the effectiveness of digital solutions themselves. By embedding rigorous quality controls, harmonised artefacts, and iterative feedback loops into routine workflows, institutions can generate more stable evidence, support fairer evaluations, and enable digital tools to deliver clearer value for diverse user groups and contexts.

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