Measuring Livestock: A Review of Data Gaps and Methodological Opportunities for Livestock Data Collection in Household and Agricultural Surveys

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Abstract

This review identifies key data gaps and methodological challenges in collecting data on livestock in the context of household and agricultural surveys, with emphasis on livestock enumeration, product quantification and valuation, and labor. Drawing on consultations with international experts and stakeholders, as well as a review of nine prominent survey instruments, including those from the 50x2030 Initiative, the Living Standards Measurement Study–Integrated Surveys on Agriculture (LSMS-ISA), and the Agricultural Integrated Survey (AGRIS), the review highlights critical gaps in measuring live weight, milk production, by-products, and gender-disaggregated labor in addition to revealing limited or inconsistent coverage in critical areas such as herd dynamics, livestock systems, feed, and animal health. The review also indicates emerging methodologies—including digital apps, AI-powered computer vision, mechanized tools, and remote sensing—and discusses their feasibility for integration in large-scale household and agricultural survey operations. The objective of the review is to inform future methodological research efforts aimed at validating scalable and cost-effective innovations for improved livestock data collected through national agricultural surveys, such as those supported by the 50x2030 Initiative.

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1. Introduction

Livestock plays a vital role in the global economy, supporting the livelihoods of at least 1.3 billion people (FAO, 2025). This sector is particularly important in the developing world, contributing to one third of agricultural production and providing a source of income to nearly 600 million of the world's poorest households (FAO, 2009; GSARS FAO, 2018). Beyond income, livestock contributes to food security, employment, land preparation, and nutrient cycling through manure (Pica-Ciamarra et al., 2014; Zane & Pica-Ciamarra, 2021). However, despite its economic and societal importance, livestock data is limited and often inaccurate, limiting policy design and implementation (Abay et al., 2025; Zezza et al., 2016).

A key reason for this gap is the historical emphasis of agricultural data systems on crop production, with livestock often treated as a secondary priority (Carletto et al., 2021). As a result, the tools and methodologies for accurately measuring livestock production systems are limited. While national statistics offices measure livestock production systems with a variety of livestock-related indicators, their quality is often challenged, even in basic indicators such as livestock numbers (Abay et al., 2025; Pica-Ciamarra et al., 2014). This challenge is exacerbated by the adoption of data collection guidelines designed uniquely to capture sedentary livestock keepers and applied to regions with a variety of livestock producing systems (Zezza et al., 2016).

Improving the measurement of livestock systems —including enumeration, product quantification and valuation (milk, meat, and by-products), as well as labor inputs— is instrumental to both economic and development planning. Accurate data enables a more complete understanding of livestock's contribution to rural livelihoods and national economies, allowing for more precise estimation of productivity, food security, and income generation. It also improves the visibility of undercounted or unpaid labor, particularly the contributions of women and youth, which are critical to designing inclusive agricultural policies. Reliable livestock data are essential for designing effective, evidence-based policies and public investments in agriculture (GSARS FAO, 2018), enabling better resource targeting and delivery of services in livestock-dependent regions.

High-quality livestock data is equally important for addressing environmental and climate challenges. Estimates of greenhouse gas (GHG) emissions from the livestock sector vary, with some studies attributing 14.9% percent of all human-induced greenhouse gas emissions globally to the livestock supply chain, with beef and dairy cattle responsible for over 60% of these emissions (Gerber et al., 2013). More recent studies suggest that livestock-related emissions could range from 19.2% to 30.3% of total anthropogenic emissions (Regan et al., 2021; Xu et al., 2021). Without accurate data on herd sizes, feed intake, and productivity levels, it is difficult to credibly assess emissions baselines or evaluate the potential of mitigation strategies such as feed additives, genetic improvements, or changes in herd management. Moreover, as international interest grows in market-based approaches such as methane cap-and-trade systems, robust and scalable livestock data will be key to ensure integrity and equity in their implementation.

Finally, better data can support adaptive responses to climate shocks. Informed by timely and accurate livestock indicators, governments and humanitarian actors can design more effective safety nets, early warning systems, and anticipatory transfers tailored to livestock-dependent households (Pople et al., 2020; WFP, 2024). Accurate livestock measurement is not only a technical challenge, but also a key input for sustainable and inclusive rural development.

This document presents a literature review identifying the main measurement practices and challenges across key domains of livestock production. The review focuses primarily, though not exclusively, on three core areas: livestock enumeration, the quantification and valuation of livestock products, and livestock-related labor. It is further complemented by insights gathered through consultations with stakeholders, which helped validate the findings from the literature review and highlight other emerging priorities (e.g. livestock production systems, feed and water access, animal health, and breeding practices). Building on these assessments, a data gap analysis is derived from a review of nine household survey instruments, including the Living Standards Measurement Study–Integrated Surveys on Agriculture (LSMS-ISA), the Agricultural Integrated Survey (AGRIS), and the Rural Household Multi-Indicator Survey (RhoMIS). Finally, the document identifies promising methodologies and innovations to address key gaps and discusses their feasibility for integration into large-scale household and agricultural survey programs. The overall goal is to inform the development of scalable and cost-effective solutions to close livestock data gaps and support the design of survey experiments aiming to improve livestock measurement in the context of the 50x2030 initiative.

2. Literature Review on Livestock Measurement

2.1. Current Practices and Challenges

Accurate and timely data on livestock is crucial for understanding rural livelihoods and informing and designing effective public policies in the agricultural sector. This is particularly relevant in developing countries, where nearly 60% of rural households are partially or fully dependent on livestock for their livelihoods (GSARS FAO, 2018). Household surveys, particularly those with multipurpose agricultural modules such as the LSMS-ISA, remain one of the most widely used tools for collecting such information due to their cost-effectiveness and logistical practicality (Fraval et al., 2019; GSARS FAO, 2018). These surveys are typically carried out face-to-face, although phone surveys have surged as a feasible alternative or complementary mode of data collection (Arthi et al., 2018; Zezza et al., 2023).

Besides household surveys, livestock data is also generated through agricultural and livestock censuses (typically conducted every 10 years), administrative records maintained by veterinary and agricultural services, and manual head counts at aggregation points such as markets or watering sites (Keita et al., 2017; Ocholla et al., 2024; Pica-Ciamarra et al., 2014). In some cases, Technical Conversion Factors (TCFs) are applied to extrapolate production values from basic livestock counts (GSARS FAO, 2018).

Despite these efforts, collecting reliable livestock data remains challenging. Herd structures are dynamic, ownership may be unclear within households, and livestock mobility, especially in pastoral and agro-pastoral systems, makes enumeration and data collection more challenging (Baker et al., 2017; Zezza et al., 2016). The following sections describe the current methodologies used to collect data on livestock enumeration, the quantification and valuation of livestock products, and livestock-related labor, highlighting the main challenges faced.

2.1.1. Livestock enumeration

The enumeration of livestock in household surveys primarily relies on self-reported data collected through face-to-face interviews. Enumerators typically ask respondents to report the number of animals the household currently owns, often disaggregated by species, breed, sex, or age (GSARS FAO, 2018). While this method is widely adopted due to its scalability and integration into standard nationally representative household surveys, recent studies have shown that it presents important limitations in terms of accuracy and reliability. For instance, Abay et al. (2025) find that cattle physical headcounts increase reported cattle numbers by 39% compared to self-reports. According to the authors, there are many sources that could explain these discrepancies, including strategic misreporting motivated by fear of taxation, loss of eligibility for government programs, and problems related to recall biases and confusion over animal classification. As many of these errors are likely to be intentional, they result in systematic underreporting, introducing non-classical measurement errors that bias estimates. These biases could lead to poorly targeted or ineffective policy responses. Further research is needed to better understand the underlying reasons for misreporting and to develop scalable data collection methods that avoid systematic misreporting.

There are several additional structural and practical challenges that further complicate livestock enumeration measurement. First, livestock are often managed by multiple members of a household, yet survey respondents (usually the household head) may lack full information, especially when animals are managed by other members or hired labor (GSARS FAO, 2018; Pica-Ciamarra et al., 2014). Second, the dynamic nature of livestock holdings, with frequent births, deaths, sales, and purchases, makes it difficult to obtain an accurate snapshot of herd size at the time of interview (GSARS FAO, 2018). Third, numeracy and literacy constraints can lead to aggregation errors, especially when respondents need to report across multiple animal categories (Dillon & Mensah, 2024). These challenges are exacerbated by the livestock system at place. In pastoral contexts, livestock mobility and seasonal transhumance make conventional sampling frames inadequate (GSARS FAO, 2018). Even when household surveys do reach these populations, current tools often fail to fully capture their livelihoods, as they are designed for sedentary systems (Zezza et al., 2016). Livestock enumeration measurement issues affect the accuracy of livestock production statistics, GDP estimates, climate impact assessments, and valuation of products, as head counts serve as the basic statistic for all these indicators.

2.1.2. Quantification and Valuation of Livestock Products

Milk production

Milk production data are most commonly collected through self-reported recall methods in household surveys. These methods ask farmers to estimate their milk off-take either at specific points in time, such as at the time of the survey or at distinct stages in the lactation cycle, or over broader periods, such as monthly or annual averages (Migose et al., 2020). Two of the most used approaches in survey settings are the Lactation Curve (LC) method and the Average Milk per Day (AMD) method. The LC approach attempts to reconstruct milk output by asking about off-take during various lactation stages, while AMD focuses on the average daily milk production over a reference period. Despite relying on memory, these recall techniques have been shown to provide reasonably accurate estimates. For example, Zezza et al. (2016) found that AMD methods (for 6 and 12 months) perform better than the LC methods in Niger. However, studies show that recall methods often underperform compared to even sparse objective records. Migose et al. (2020), for instance, demonstrated that limited test-day and single test-day records outperformed simple recall methods for both herd- and cow-level milk yield estimation in Kenya.

More accurate measurements of milk production per lactation (MPL) are generally obtained through regular longitudinal recording, where milk output is tracked repeatedly throughout the lactation cycle. This is common in more commercialized or larger-scale systems with standardized management and milking routines. However, in smallholder contexts such regular recording is rare due to infrastructure constraints, high labor demand, and limited incentives for farmers to maintain records (Daum et al., 2022). Test-day methods offer a middle ground as they involve periodic measurement (e.g., monthly) of milk production per cow. Migose et al. (2020) showed that even limited test-day recording of three or four times per lactation period can provide significantly better estimates than recall-based approaches. Nevertheless, implementing test-day systems is also costly and labor-intensive, limiting their feasibility for large-scale survey operations.

There are several factors that make the measurement of milk production particularly challenging in surveys. First, milk yield varies substantially depending on the lactation stage, and is influenced by seasonality, animal health, and feeding conditions. Secondly, not all lactating cows are milked consistently: some milk is left for suckling calves, or cows may temporarily stop lactating. This introduces substantial heterogeneity and potential misreporting, particularly when respondents estimate average production without clear reference periods (Zezza et al., 2016). Additionally, milking complicates quantification in contexts that lack standardized measuring equipment (Kaunkid et al., 2022). During policy interventions, recall data may also be influenced by social desirability bias, as farmers might overstate production in response to perceived program expectations. To mitigate this, some studies have used para-veterinarians or trained third parties to verify production (Behaghel et al., 2020).

Meat production

While essential for understanding livestock productivity, cattle weight data remains scarce. A key reason for this scarcity is the poor quality of available data. As with enumeration and milk production, live weight data is primarily collected through household surveys and agricultural censuses. However, farmer-reported weight estimates are often unreliable. As a result, many countries have stopped collecting weight data directly from farmers, instead resorting to average weight estimates by livestock category (e.g., age, sex, breed) derived from better-controlled environments such as markets or slaughterhouses (GSARS FAO, 2018).

Although livestock markets and slaughterhouses offer a useful source of live weight data, on-farm measurements are essential for accurately estimating livestock assets at the household level. Tools such as weighing scales and weight tapes, which use girth measurements to estimate weight, have been proposed as practical alternatives. Yet, these methods are labor-intensive, costly, and can cause animal stress, potentially reducing weight and productivity. In extensive grazing systems, selecting which animals to weigh also presents sampling challenges, requiring enumerators to follow standardized protocols to ensure data representativeness (GSARS FAO, 2018; Dang et al., 2022).

To reduce costs and stress, automated weighing systems have become more common, especially on larger farms. These include walk-over weighing (WoW) systems, where animals walk entirely over a sensor platform (Parsons et al., 2023), and step-on–off (SOO) systems, such as the Optiweigh, which estimate full-body weight by measuring only a part of the animal, typically the front legs (Hasan et al., 2024). While these systems allow for frequent, automated, and less labor-intensive data collection, they require technical infrastructure like enclosures, making them better suited to semi-intensive or fenced systems. Moreover, because animal entry into the weighing platform is voluntary, these systems may introduce sample selection bias and non-random missing data (Hasan et al., 2024).

Livestock by-products

Derived livestock products, such as manure, animal draught power, transport services, savings and insurance functions, and social capital, represent approximately 50% of livestock's total contribution to household livelihoods (Zane & Pica-Ciamarra, 2021). Despite their significance, these non-tradable outputs are rarely well captured in agricultural surveys. When they are included, survey questions tend to be limited in scope and often fail to gather information on quantities or economic value, making it difficult to estimate their true contribution to household welfare. Further research is needed to develop survey tools that can systematically and accurately measure these derived products.

A word on conversion factors

As mentioned before, conversion factors are commonly used to estimate production levels and economic value based on livestock headcounts. However, while enumeration may already introduce bias due to systematic underreporting, the use of conversion factors adds an additional layer of potential mismeasurement. Conversion factors are often outdated or not calibrated to local breeds and conditions, increasing inaccuracies in productivity and economic valuation metrics (GSARS FAO, 2018; Zane & Pica-Ciamarra, 2021). Further research in this area to validate and update conversion factors could greatly benefit livestock valuation and quantification measurement.

2.1.3. Livestock Labor Measurement

Measuring labor in livestock activities shares many of the same challenges found in crop agriculture, including recall bias, seasonality, and gendered task allocation. However, livestock labor receives considerably less attention in household surveys. It is often grouped under general agricultural tasks, with livestock tending listed as just one among many activities (Durazo et al., 2021). Some surveys measure it indirectly through questions to catch underreported work, yet these tend to lump livestock together with broader agricultural or household categories. As a result, the literature explicitly addressing livestock labor data collection remains limited.

Like in crop-related labor, recall bias is significant, especially because livestock tasks are continuous and often low in salience. This can lead to overestimation (Arthi et al., 2018) or omission of irregular or marginal contributions, such as when children or women feed animals while performing other duties. These simultaneity issues make accurate time-use reporting difficult (Durazo et al., 2021). Livestock labor is also sensitive to seasonality, making reporting sensitive to the timing of the interview (Gaddis et al., 2023). Mixed herding systems and shared responsibilities further complicate labor attribution. Most surveys fail to differentiate between labor for feeding, herding, milking, and veterinary care, which greatly varies depending on the livestock system at place (GSARS FAO, 2018).

To improve measurement, some studies have employed time-use diaries and accelerometers (Friedman et al., 2023). However, capturing livestock labor remains difficult, especially given the multitasking nature of these activities. Gender livestock labor specialization further complicates reporting as some of their activities may be undervalued or unrecorded (Gaddis et al., 2023). Gender-disaggregated labor inputs, essential to understanding women's role in livestock production, are especially underreported (Pica-Ciamarra et al., 2014). Importantly, this literature review found no experimental study directly addressing the unique challenges of measuring livestock-specific labor.

3. Data Gap Analysis

3.1. Review of Existing Household Surveys

The data gap analysis was guided by two main sources of information: stakeholder consultations and the literature review. The stakeholder consultations involved discussions with over 20 specialized teams from international organizations, including the World Bank, FAO, and IFAD; representatives from national, regional, and international research institutes such as KALRO, NARO, AU-IBAR, SEBI-Livestock, ILRI, IFPRI, TALIRI, and Development Gateway; as well as university-affiliated researchers from institutions including Cornell, Wageningen, Edinburgh, Wisconsin, Makerere, Minnesota, and PSE/CGIAR-SPIA.[2] On the other hand, the literature review encompassed published articles, working papers, and grey literature, resulting in the systematization of insights from more than 35 sources.

The outcome of these exercises was the identification of 31 domains, focusing on four main thematic areas: livestock enumeration, quantification of livestock products, valuation of livestock products, and livestock labor. Based on the list of domains, nine key survey instruments were analyzed: the Tanzania National Panel Survey (NPS 2020/2021), Annual Agricultural Sample Survey (AASS 2023), and National Sample Census of Agriculture (NSCA 2019/2020), the Burkina Faso's *Enquête Harmonisée sur les Conditions de Vie des Ménages* (EHCVM 2021/2022), the Uganda National Panel Survey (UNPS 2019/2020), the 50x2030 Initiative's Core Questionnaire (v.5), the Agricultural Integrated Survey (AGRIS 2018), the Rural Household Multi-Indicator Survey (RHoMIS v.1.6), and the Index-Based Livestock Insurance (IBLI v.12) data collection tools. These instruments were selected as they represent some of the most comprehensive surveys available for livestock data collection, and due to their suitability for contexts relevant to this analysis. A matrix summarizing the content of the domains of interest across the nine surveys, discussed in detail below, is available in the supplementary material.

Despite differences in design and scope, these surveys share several features. Most include livestock modules embedded within broader agricultural or household surveys, typically relying on face-to-face interviews. They commonly adopt a 12-month reference period for key livestock variables, allowing consistency in comparisons over time and across regions. The surveys often collect data on livestock

[2] Acronyms are defined as follows: United Nations Food and Agriculture Organization (FAO); International Fund for Agricultural Development (IFAD); Kenya Agriculture and Livestock Research Organization (KALRO); Uganda National Agricultural Research Organization (NARO); African Union Inter-African Bureau for Animal Resources (AU-IBAR); Center for Supporting Evidence-Based Interventions in Livestock (SEBI-Livestock); International Livestock Research Institute (ILRI); International Food Policy Research Institute (IFPRI); Tanzania Livestock Research Institute (TALIRI); Paris School of Economics (PSE); CGIAR Standing Panel on Impact Assessment (CGIAR-SPIA).

ownership, herd size, production levels (especially for milk and meat), and the domestic and commercial use of livestock products. Many instruments also integrate questions on household demographics, agricultural practices, and community-level characteristics, providing valuable context for interpreting livestock-related data. However, significant gaps remain in their ability to capture nuanced dimensions such as shared ownership arrangements, herd dynamics, detailed labor inputs, and market-related variables like price seasonality and product quality. It is important to note that, as multipurpose instruments, these surveys are not designed to comprehensively capture all dimensions of livestock-related activities. The next sections provide a detailed explanation of these data gaps, discussing whether and how they are addressed by the instruments, and highlighting the tools that offer the most comprehensive information for each domain.

3.2. Identified Data Gaps

3.2.1. Livestock Enumeration

The main data gaps identified with respect to livestock enumeration concern the consistency of livestock data filters, the lack of accurate livestock counts, limited information on shared ownership, and the inadequate capture of livestock transitions and herd structural changes.

Among the surveys analyzed, two primary criteria are used to determine which households proceed to the livestock module: ownership and activity. Of the nine surveys reviewed, two filter households based solely on ownership, three include either ownership or activity, while the remaining four filter households based on activity regardless of ownership status. The typical approach is to ask about any livestock ownership in the past 12 months. The heterogeneity in filtering criteria can lead to inconsistencies in the data, as different types of households may be included or excluded across surveys. Notably, such heterogeneity appears not only across countries but also within countries. For example, the three questionnaires analyzed for Tanzania apply these three different filtering approaches (ownership only; ownership or activity; and activity irrespective of ownership), potentially leading to different aggregate livestock statistics.

Livestock counts in surveys rely on farmers' self-reporting. Most instruments first ask about the total number of livestock kept, followed by the number specifically owned by the household. The prevalent approach is to follow the same ownership/activity criteria used for filtering, although some exceptions exist. For instance, in the Tanzania NPS, the initial filter is ownership. However, subsequent questions address both ownership and livestock raised. Typically, data are collected with differentiation by livestock species (cattle, goats, sheep) and by breed type (traditional or improved/exotic). More specialized surveys, such as the Tanzania NSCA, further disaggregate data by detailed categories like castrated bulls (oxen), uncastrated bulls, cows, steers, heifers, male calves, and female calves, including categories for improved breeds by purpose (beef vs. dairy). In terms of timing, the most common practice is to ask about the current number of animals.

Regarding shared ownership, only three out of the nine instruments contain additional questions beyond the initial filter to capture ownership differences. These surveys, which begin by screening households for animals kept or owned, then ask whether all the cattle kept actually belong to the household. The Burkina Faso EHCVM instrument goes further by asking about different household members' ownership and decision-making authority over livestock sales. The most comprehensive instrument is found in the UNPS, which includes detailed questions on which household members own livestock, who manages them, whether animals are kept outside the household, and whether the household is managing livestock not owned by any of its members.

Stakeholders have also highlighted significant difficulties in tracking herd dynamics. As mentioned before, most instruments employ a 12-month recall period as the reference frame, collecting information on changes in herd size due to births, purchases, gifts, sales, use as payments, losses from disease, theft, injuries, natural disasters, or slaughter. The most comprehensive instruments, such as the Tanzania NSCA, go a step further by disaggregating these events by specific animal categories (e.g., castrated bulls, uncastrated bulls, cows, steers, heifers, male calves, female calves).

Questions to directly capture herd structural transitions, such as changes in herd composition over time or shifts between different livestock uses, were not found on the instruments reviewed. The closest approximation to such data comes from the Tanzania NSCA, thanks to its detailed disaggregation by livestock type, though this still falls short of capturing dynamic herd transitions explicitly.

3.2.2. Quantification of Livestock Products

The main data gaps identified in the quantification of livestock products include animal live weight, milk production, meat production, and livestock by-products such as manure, skins, hauling services, and draught power.

As highlighted in the GSARS FAO (2018) guidelines, animal weights have often been neglected in household surveys due to unreliable self-reported data. This is reflected in the surveys reviewed, where none include questions about the live weight of animals currently owned. Instead, at least three instruments collect information on the live weight of animals at the time of slaughter, when farmers are more likely to weigh animals and recall accurate figures. Nevertheless, improving data on live animal weight remains essential, as it is a crucial input for calculating productivity gains and profit margins in livestock production.

Both milk and meat production questions focus on capturing quantities and value. Milk production is generally measured using the average milk per day method based on three core questions: (i) the number of animals milked during the reference period (usually 12 months), (ii) the number of months the animals were milked, and (iii) the average daily quantity of milk produced. Another common question concerns whether calves were suckling during the milking period, which affects milk offtake. Surveys routinely include questions about the destination of milk—whether consumed by the household, sold, or processed into other products. Price information and sales of the milk produced are also usually captured. In addition to milk production, the surveys capture milk consumption through 7-day recall periods, where households are required to list quantities consumed and prices paid for milk purchases. More specialized instruments delve deeper into milk production details. For example, the AGRIS core module gathers information about the lactation period, while the RHoMIS survey explores potential variations in average milk production by asking respondents about periods when cows were producing well versus periods when they were not.

In the case of meat, the common practice is to record the number of animals slaughtered over the past 12 months. Subsequent questions often capture the value of sales and household earnings from meat production. The Burkina Faso EHCVM survey goes even further by collecting detailed data on meat production costs. More specialized surveys, such as the AGRIS core module, include questions about carcass weight and data quality (i.e., whether weights are estimated or measured). These surveys also inquire about the final use of meat products, distinguishing between own consumption, market sales, and payments in kind. Similarly to the case of milk, household surveys frequently include questions on meat consumption using a 7-day recall period and capturing quantities and prices of meat consumed, including meat sourced from the household's own production.

Three livestock by-products were identified as having significant data gaps: manure, skins, and hauling services and draught power.

Regarding manure, all but one of the reviewed instruments include some questions on this topic. However, questionnaires vary in whether they focus on manure production, its use, or both. The status quo generally consists of asking about the use of dung produced by animals over the past year or agricultural season. Notably, the Tanzania AASS and the 50x2030 Core questionnaire include questions specifically about manure production and quantities. The AGRIS core module is the most detailed in this domain, collecting information on dung production timing, storage practices, and the quantities of manure used for purposes such as fuel or construction.

Only five out of the nine surveys collect relevant data on skins. Of these five, three are specialized instruments (the Tanzania AASS, the Tanzania NSCA, and the AGRIS core module), while only the Tanzania NPS and the Burkina Faso EHCVM capture this information. Typically, these surveys collect data on skin production, including quantities and prices.

Finally, hauling services and draught power are addressed in six of the nine instruments reviewed. These surveys typically ask whether households have used livestock for transport or for ploughing fields during the past 12 months. Some surveys also collect data on the number of animals used for such activities.

3.2.3. Valuation of Livestock Products

One of the main data gaps identified for the valuation of livestock products is the lack of detailed market information. While most instruments include some variables aimed at capturing market availability and prices, there is considerable heterogeneity in how this information is collected. Typically, market availability and prices are gathered through community questionnaires. Instruments that collect market data at the household level often ask about average prices for livestock sold or purchased during the reference period. Among these, the Tanzania NPS is one of the most comprehensive, as it includes values related to purchases, losses due to disease, theft, injuries, sales, and livestock slaughtered.

None of the reviewed questionnaires collect data on critical market aspects such as seasonal variations in animal prices, characteristics that influence price differences within livestock categories, variations in animal weight gains and losses, or the quality of livestock products. These remain important gaps that need to be addressed for a more accurate valuation of livestock assets and production.

In the context of valuing livestock by-products, instruments generally capture the value of outputs like manure, skins, and draught power by recording both quantities and associated values. For manure, tools typically collect data on the total value of sales during the reference period, with the 50x2030 Core instrument going further to include average unit prices. Regarding skins, out of the five surveys that collected data on this by-product, only three recorded both quantities and prices. For draught power, only one instrument included questions about the income earned from providing these services to other households.

3.2.4. Livestock Labor Measurement

Three main gaps have been identified regarding livestock labor: the lack of detailed information on the type and duration of labor activities, limited data on shared arrangements for livestock rearing, and insufficient disaggregation to capture the labor contributions of women and youth.

There is significant heterogeneity in how livestock labor is captured across survey instruments. The most common approach is to include livestock-related tasks within the broader list of potential household activities. Instruments often collect information on the time devoted to these tasks, measured in months and hours per day. Typically, questionnaires inquire about the primary individual responsible for livestock care, rather than collecting data from all household members.

Some tools, such as the Tanzania NPS and the NSCA, collect more detailed information on specific activities related to livestock rearing, including tasks like feeding, grazing, and selling animals. Importantly, the NSCA gathers this information disaggregated by livestock type. Both the Tanzania NPS and the UNPS also collect data on hired labor, including payments and time devoted to livestock activities. The AGRIS core module is the most comprehensive among the reviewed instruments as it contains a highly detailed breakdown of labor activities and recording both months and days worked for family members and hired laborers.

The second key data gap relates to shared or informal arrangements in livestock rearing. While several surveys capture data on hired labor, they often do not explicitly address informal labor-sharing practices. Only two of the nine instruments include questions on this topic. The Tanzania AASS collects information on external labor, distinguishing between free workers, exchange workers, and hired workers, and gathers details about the duration of external labor contributions and payments made in cash or kind. The second tool addressing shared livestock rearing is the RHoMIS, which collects information on whether external individuals (without specifying their status) worked on the household's land. It records labor arrangements involving family, friends, neighbors, and hired workers.

Given the gendered nature of livestock rearing, where men often focus on large ruminants and women and youth typically manage small ruminants, disaggregating data by gender and age is essential. However, this remains a notable data gap. Only three of the nine instruments reviewed collect information that allows such disaggregation. The 50x2030 Core questionnaire asks explicitly about the managers of different livestock types, offering response options for men, women, and children. Although the Tanzania NSCA and the AGRIS core module do not directly inquire about the roles of women and youth, they collect detailed information on various livestock activities disaggregated by species, which can indirectly facilitate analysis of gender and child labor participation.

3.2.5. Additional Data Gaps

Stakeholder consultations and the literature review highlighted several additional data gaps that should be addressed to ensure an accurate representation of livestock keepers' livelihoods and well-being. These gaps can be grouped into three main categories: information on livestock systems, feed and water for animals, and animal health.

There is broad consensus on the need to better characterize livestock systems, particularly because household questionnaires often fail to adequately capture nomadic and semi-nomadic pastoralist groups. The primary method for characterizing livestock systems is through information about major feeding practices. Only three of the nine instruments reviewed included questions on this topic (the Tanzania NPS, the UNPS, and the AGRIS Core Module). Additionally, the community questionnaire in the Tanzania NPS collects data on whether village residents migrate with their livestock, including information on destinations and timeframes. The Tanzania NSCA offers an alternative approach by asking about the type of agricultural activity practiced, with an explicit option for pastoralism.

Feed and fodder data are collected by eight out of nine instruments. The prevailing practice is to ask households whether they purchased any fodder in the past 12 months, including details about the months of purchase and associated costs. More specialized surveys, such as the Tanzania AASS, gather more detailed data on feed types, including crop residues, industrial by-products, balanced concentrates, and feed supplements. Additionally, agricultural sections of household surveys often collect information on the use of crop residues as animal feed. Finally, community-level information on grazing lands and communal pastures is captured by some of the instruments such as the Tanzania NPS, Burkina Faso EHCVM, and the UNPS.

A significant data gap remains regarding feed and fodder quality, which none of the reviewed instruments address.

Five instruments include questions about water for animals. Two focus uniquely on the costs associated with watering, collecting data on expenditure amounts and durations. The other instruments go further, gathering information on water availability, frequency of watering, main water sources, and prices.

Regarding animal health, all but two questionnaires collect information on the prevention and treatment of livestock diseases. For prevention, the standard approach includes collecting data on common livestock diseases, vaccination and deworming practices, and the presence of extension workers or veterinarians. These questions capture details about disease types, vaccination and deworming status, and associated costs. For treatment, instruments gather data on costs related to curative measures for each livestock type during the reference period.

Only the Tanzanian census includes detailed questions on animal disease outbreaks, recording the number of animals infected, treated, recovered, or deceased during the past year, disaggregated by livestock type.

Information on breeding activities is collected by four of the instruments. Typically, surveys inquire whether households practiced controlled mating or breeding strategies during the reference period, and request details on the specific methods used. More specialized surveys also collect data on the costs and earnings associated with breeding practices and identify the providers of these services.

3.3. Lessons for Priority Areas for Improvement

3.3.1. Livestock Enumeration

Livestock enumeration would benefit from harmonizing survey filters used to identify livestock-keeping households. As previously mentioned, in Tanzania, different instruments apply varying criteria —some based on ownership alone, others on activity, or on both— which could lead to inconsistencies in livestock statistics and limits the possibility of cross-validation across datasets. Regarding livestock enumeration, currently livestock counts rely entirely on households' self-reported data, which can result in significant inaccuracies due to intentional or unintentional misreporting, as shown by Abay et al. (2025). This highlights the need for exploring objective enumeration methods, such as physical headcounts or technological solutions, to improve accuracy. For pastoralist populations, it is crucial to include questions on satellite camps where households may keep parts of their herds, to ensure complete enumeration. Shared ownership of livestock is also insufficiently addressed in many instruments, distinguishing between animals merely kept versus fully owned by households is essential for accurate welfare and asset assessments. While most instruments do collect data on livestock dynamics, the common use of a 12-month recall period poses challenges due to potential recall bias, particularly given the complexity of tracking numerous inflows and outflows in herd composition. Further methodological research is needed to address the accuracy of these measures and evaluate the potential challenges arising due to recall bias. Finally, there is a significant gap regarding herd structural changes, as none of the instruments capture the dynamics in herd composition by age, sex, or purpose over time, hiding important variations relevant to understanding household livelihoods and resilience.

3.3.2. Quantification of Livestock Products

Animal live weight remains one of the most critical and persistent data gaps in livestock statistics, limiting the accuracy of productivity and valuation estimates. This gap highlights the need to explore objective, cost-effective methods for measuring weight at the household level. Regarding meat production, while most instruments capture data on the number of animals slaughtered and income earned from sales, there is limited information on production costs, which would be valuable for estimating economic returns. For milk production, current surveys generally gather data on average daily milk yield, the number of animals milked, and the duration of milking, usually over a 12-month reference period. Although evidence suggests that the average daily milk yield approach is more accurate than lactation curve methods, significant recall bias may arise over long periods. Studies by Zezza et al. (2016) and Migose et al. (2020) indicate that shorter recall periods could enhance accuracy, suggesting that surveys should consider more frequent data collection to better reflect milk production dynamics. In the domain of livestock by-products, while most instruments ask about manure use or production, gaps remain regarding the quantities produced, storage practices, and commercial sales, which are essential for fully valuing livestock's contribution to farm systems. Skins represent another notable data gap, as few surveys inquire about this output.

3.3.3. Valuation of Livestock Products

While market information is generally collected across surveys, there is significant heterogeneity in the level of detail and approaches used. The Tanzania NPS provides a comprehensive market module that could serve as a valuable model for other instruments seeking to improve market data collection. There are several key gaps that need to be addressed. Most surveys do not capture seasonal variations in animal prices, nor do they consistently collect data on animal characteristics related with prices, such as breed, age, or condition. Prices disaggregated by categories within species are also largely absent, limiting the ability to understand the economic dynamics of livestock markets and their implications for household livelihoods. Although surveys often include questions on the value of by-products when these are available, critical gaps persist around measuring weight gains or losses in animals and their effect on prices.

3.3.4. Livestock Labor Measurement

Livestock labor remains an area with notable gaps in data collection. Information on shared labor arrangements, such as informal exchanges of labor between households or communities, is rarely captured, yet it is critical for understanding the true costs and labor dynamics of livestock rearing. Without this data, some economic and social costs remain hidden, leading to incomplete analyses of household livelihoods and production systems. Additionally, gender and youth labor in livestock activities are insufficiently documented in most survey instruments. This is a significant omission, as women and youth often contribute substantially to tasks such as feeding, herding, milking, and caring for smaller livestock species.

3.3.5. Additional Data Gaps

Several important livestock data collection gaps have been highlighted beyond core areas of enumeration, quantification and valuation, and labor. One critical gap concerns the proper characterization of livestock production systems. Surveys often lack sufficient detail to identify pastoralist, semi-nomadic, or other specialized systems, despite the significant share of pastoralists in African livestock economies. This omission limits the ability to tailor interventions and accurately reflect the livelihoods of these groups.

With respect to feed and fodder, while most surveys gather data on quantities purchased or produced, crucial gaps persist regarding feed quality. Understanding feed quality is essential, as it directly influences livestock productivity, weight gains, and environmental impacts such as greenhouse gas emissions.

Animal health data are relatively well-covered in terms of preventive measures and treatment practices, but significant gaps remain regarding disease outbreaks. Only one of the reviewed instruments collected detailed data on livestock disease occurrences and outcomes. Addressing these gaps would enhance the capacity to monitor animal health risks and design timely interventions.

4. Identification of Potential Methodologies and Innovations

Several innovations have been developed to improve livestock production measurement. These innovations mainly focus on improving the quality, reliability, and frequency of livestock data. Broadly, these solutions can be grouped into four main categories: (1) digital applications that support real-time data entry and management at the farm level, (2) artificial intelligence tools, particularly computer vision, that enable non-invasive estimation of livestock characteristics, (3) mechanized innovations that automate the collection of production data such as milk yield and live weight, and (4) remote sensing-based approaches that offer scalable solutions for livestock and rangeland monitoring. This section details the main contributions of each category, detailing examples of ongoing applications and relevant evidence from the literature.

4.1. Digital Applications for Farm-Level Livestock Data Management

Digital applications are among the most actively explored innovations for improving livestock management through more frequent data collection. These tools are typically designed to help farmers track key management aspects such as animal identification and registration, traceability, animal health records, and performance monitoring (Resti et al., 2024). In many cases, record-keeping functionalities are integrated with additional features like decision-support tools and extension services. Several recent developments across sub-Saharan Africa and South Asia have shown encouraging results in enhancing the efficiency and timeliness of data flows in livestock systems (Daum et al., 2022; Gwaka, 2022).

There is some encouraging evidence of their effectiveness. Field-based studies have shown that digital apps can significantly improve the timeliness, accuracy, and completeness of animal disease reporting. For instance, Beyene et al. (2018) found that the VetAfrica–Ethiopia app enabled faster and more complete reporting compared to traditional paper-based systems, with disease reports submitted within 2 to 13 days depending on internet access (compared to 30-days under traditional systems). Beyond disease surveillance, digital applications have also shown potential to improve recordkeeping related to milk production, herd composition, and input use (Resti et al., 2024).

However, most of these applications rely on manual data entry via smartphones, which limits their uptake and compromises data accuracy. Given this reliance, the success of digital apps heavily depends on sustained user engagement. For example, in India, the Herdman app failed to achieve continued adoption due to a lack of meaningful incentives for farmers to consistently input milk data (Daum et al., 2022). Moreover, only a few applications have been co-developed with end users, with iCow being a notable exception.

In addition, the large adoption of these apps faces several challenges. First, their use is constrained by poor internet connectivity, lack of training, and limited integration with national information systems. Many of these tools remain in early or experimental phases, often developed by researchers with limited scalability plans. On the user side, barriers such as low digital literacy, distrust of technology, unclear benefits of data entry, and language limitations reduce engagement. In several documented cases, outdated or non-contextual advisory content and poor user interfaces further undermined usability (Daum et al., 2022; Resti et al., 2024).

Examples of existing applications include:

- Livestock247 (Nigeria): A digital livestock marketplace and health service platform.
- Stellapps (India): A comprehensive dairy ecosystem offering recordkeeping, advisory, and smart sensors.
- Kaznet (East Africa): An Android-based app and web platform developed by ILRI, designed for data collection (markets, households, rangelands) via micro-tasking in pastoralist settings.
- iCow (Kenya): A bundled service providing recordkeeping, SMS-based advice, and herd tracking.
- DigiCow (Kenya): A digital advisory app for dairy farmers focused on digitizing farm records.
- Jaguza Tech (Uganda): AI-powered livestock management offering smart sensors and analytics.
- M-nomad (Kenya): An online livestock marketplace linking pastoralists with buyers.

4.2. Artificial Intelligence and Computer Vision

Artificial intelligence (AI), particularly through computer vision and machine learning, has been applied to improve livestock measurement particularly focused on animal behavior, live weight, and tracking animal movements. The main motivation behind the development of these tools is to reduce the reliance of labor-intensive, and animal stressful procedures such as manual weighting of cattle. Moreover, they allow to have a more continuous and accurate monitoring at the farm level (Guarnido-Lopez et al., 2024).

Several studies have demonstrated the potential of computer vision to predict cattle weight with high accuracy. These systems typically use 2D or 3D cameras to capture morphometric features, including body length, heart girth, and withers height, and apply deep learning models like convolutional neural networks (CNNs), recurrent neural networks (RNNs), and artificial neural networks (ANNs) to estimate body weight. For example, Cominotte et al. (2020) found that ANN-based predictions achieved high precision in estimating body weight and average daily gain in beef cattle using 3D images from Kinect sensors. Similarly, Ruchay et al. (2022) reported a mean absolute percentage error (MAPE) of 8.4% using RGB-D imagery and 3D augmentation techniques, demonstrating 91.6% prediction accuracy. Larger literature reviews reflect these findings. Hossain et al. (2025) synthesized 53 studies and identified that body length and withers height were among the most frequently used features for cattle weight estimation. They also noted an increasing preference for 3D vision techniques, used in 21 of the reviewed studies, due to their enhanced precision.

Despite promising results, several technical and practical challenges need to be addressed to enable broader adoption. Many studies rely on small, homogeneous samples and lack standardization across data types, feature selection, and evaluation metrics (Gjergji et al., 2020; Hossain et al., 2025). Variations in cattle posture, lighting conditions, and camera positioning can introduce noise and reduce model accuracy (Ruchay et al., 2022). Additionally, the cost and setup requirements of specialized imaging systems may be impractical for smallholder farms (Bailey et al., 2018).

4.3. Mechanized Tools for Automated Livestock Data Collection

Beyond digital innovations, recent advances in mechanization have introduced practical tools aimed at enhancing the direct and automated capture of livestock production metrics. These tools offer a way to eliminate recall biases by generating objective, real-time data on key outputs such as milk yield and cattle weight.

In the area of milk production, Kaunkid et al. (2022) introduced an automated milk quantity recording system tailored for small-scale dairy farms employing bucket milking. The innovation consists of a mobile unit (a wheelbarrow equipped with a load cell weight mechanism and embedded electronics) that measures milk in kilograms during collection. Farmers can enter cow identifiers and timestamps, and the system transmits the data to the user in real time. This allows for continuous and standardized measurement of individual cow productivity, potentially improving both herd management and the accuracy of milk data production. The device's portability and ease of use make it well-suited to small-scale systems, although scaling up may be prohibitive due to the investments needed.

For the measurement of live weight, Hasan et al. (2024) evaluated a mobile in-paddock weighing platform, comparing its performance against a conventional static weighbridge across a sample of 65 mixed-breed cattle. The mobile platform demonstrated high accuracy, with only minor deviations: a tendency to slightly overestimate the weight of lighter cattle and underestimate heavier ones. Importantly, the device achieved this accuracy without inducing stress in animals or requiring additional labor for restraining or moving livestock. The technology proved robust across cattle breeds and sexes, offering a practical solution for in-field live weight monitoring. The main limitation of this tool is the sample selection it can have, as cattle self-select into measurement.

4.4. Remote Sensing for Large-Scale Livestock and Rangeland Assessment

Remote sensing has emerged as a promising complementary approach for livestock data collection, particularly in domains such as livestock enumeration and pasture monitoring. Advances in satellite and aerial imagery, combined with machine learning and computer vision techniques, have enabled researchers to explore automated methods for detecting and counting animals in open landscapes, as well as assessing the quality and availability of livestock feed resources.

In the context of livestock enumeration, recent studies have successfully applied deep learning techniques to very high-resolution imagery to estimate cattle populations. For instance, convolutional neural network (CNN)-based models such as CSRNet and LCFCN (Laradji et al., 2020) have been adapted for counting cattle herds in open rangelands. These methods operate better by estimating object densities rather than detecting individuals, which helps deal with occlusions and overlapping animals. More recently, Hodel et al. (2024) combined object detection and density estimation methods using CNNs to improve cattle recognition accuracy from remote sensing data. However, these methods often require imagery with spatial resolution finer than 50 cm per pixel. This data may not be available at a high frequency and having it available for defined time frames may be prohibitively costly.

5. Feasibility of Innovations' Implementation

While technological innovations present significant opportunities to improve livestock data collection, their feasibility and fit within large-scale household and agricultural survey frameworks such as the 50x2030 Initiative vary considerably.

Remote sensing is a promising alternative for monitoring livestock populations and rangeland conditions at regional or national scales. High-resolution satellite imagery combined with machine learning can detect and estimate large herds in open landscapes, supporting macro-level assessments of livestock distribution and environmental dynamics. These tools perform best in relatively homogeneous settings with large herds (typically over 10 animals per group) and sparse ground cover. However, these methods remain poorly suited for household-level enumeration because they cannot link observed animals to specific households or distinguish between animals of different owners in mixed-use landscapes. The high cost and limited frequency of high-resolution imagery further constrain their scalability. Therefore, while remote sensing holds strong potential to complement aggregate livestock statistics, it is not a practical solution for household-level data collection in household survey contexts.

Mechanized tools, such as automated weighing platforms and milk recording devices, demonstrate strong potential for precise and objective measurement of key livestock metrics. These tools are effective in reducing biases associated with self-reported information, improving data accuracy. However, their implementation at scale within household surveys remains challenging. The cost, technical maintenance requirements, and logistical complexities associated with deploying these devices in diverse field conditions—especially among smallholder farmers in low-resource settings—limit their applicability. Additionally, technologies like walk-over weighers rely on voluntary animal participation, potentially introducing selection biases. As a result, while mechanized tools may serve as valuable instruments for validation studies or specialized research, they are currently impractical for large-scale integration into household surveys. Nevertheless, it may be worth analyzing their use as gold-standard measures in survey experiments aimed at improving livestock measurement.

Digital applications, particularly mobile-based recordkeeping apps, have shown promise for improving data quality. These apps can facilitate high-frequency data collection and reduce reliance on memory-based recall, making them particularly valuable for tracking livestock enumeration, herd dynamics, and milk production. However, their feasibility in household survey contexts remains constrained by several factors, including variable digital literacy levels, limited smartphone penetration in rural areas, and inconsistent internet connectivity. Nevertheless, there is scope to explore digital apps as potential "diary" tools, where selected respondents could record livestock events more frequently between survey visits. This approach could significantly reduce recall bias and improve the measurement of dynamic indicators, but would require substantial piloting to assess farmers' engagement and data compliance.

Among the innovations reviewed, artificial intelligence applications, particularly computer vision for measuring livestock characteristics, appear the most promising for integration into household survey data collection. Computer vision offers a feasible way to capture livestock traits such as live weight or body condition with minimal respondent burden. Importantly, these technologies have the potential to be embedded into survey workflows, for example, through enumerator-operated mobile devices that capture animal images for automated analysis. These tools also look promising for improving livestock enumeration, with commercial initiatives such as Plainsight already demonstrating its feasibility. These tools could potentially contribute to the measurement of animal valuation, herd composition, and improved tracking of livestock dynamics.

In conclusion, while remote sensing and mechanization offer compelling solutions for specific livestock data challenges, their scale and operational requirements make them less suited for direct household-level data collection. Digital applications may hold promise for supplementing survey data through farmer diaries, but their scalability remains uncertain. By contrast, computer vision offers a promising alternative for improving livestock measurement by providing more objective data on key gaps such as live weight, herd dynamics and composition, and livestock enumeration. It also holds strong potential for integration into household survey protocols, though validation of these approaches in the context of agricultural and household surveys has yet to be rigorously undertaken.

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