# IMPACT OF MEASUREMENT ACCURACY ON Z-SCORE-BASED NUTRITIONAL CLASSIFICATION IN AN IOT-BASED ANTHROPOMETRIC MONITORING SYSTEM

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## ABSTRACT

Accurate and consistent anthropometric data are essential for reliable interpretation of toddler nutritional status based on WHO Z-score. The use of Internet of Things (IoT)-based toddler scales enables automated integration between anthropometric measurements and the data management system; however, the reliability and integrity of the generated data require systematic evaluation prior to their application in growth monitoring. This study aimed to assess the measurement performance and data integrity of an IoT-based toddler scale through standard calibration testing, as well as to examine the potential impact of measurement error on Z-score variation and nutritional status classification. An applied experimental approach was employed by adopting medical device calibration principles. The scale was tested under static conditions using reference weights and standardized measurements to evaluate the accuracy and repeatability of body weight and height measurements. Measurement data were automatically recorded, stored in a centralized databased, and analyzed for growth chart visualization and z-score-based nutritional status classification. The evaluation demonstrated a maximum measurement error of 1,25% for body weight and 0% for height measurements. Quantitative simulation indicated that a ±1,25% measurement error at a nominal body weight of 10 kg could result in a ±0,18SD variation in z-score. Such variation may lead to a shift in nutritional status classification when measurements are located near the -2SD threshold. Although the observed measurement errors were relatively small, their impact on nutritional status classification may be significant under specific conditions. Calibration-based evaluation underscores the importance of measurement accuracy and data integrity as essential prerequisites for the technical readiness of IoT-based systems to support toddler growth monitoring.

**Keywords**: Internet of Things, Toddler Growth Monitoring, Measurement Accuracy, Data Integrity, Z-Score.

## INTRODUCTION

Growth monitoring in early childhood constitutes a foundational component of preventive and promotive health care within maternal and child health services. Anthropometric indicators, particularly body weight and height, are routinely employed to evaluate physical development and nutritional adequacy in accordance with standardized growth references, most prominently the World Health Organization (WHO) Z-score system. Through indices such as weight-for-age, height-for-age, and weight-for-height; Z-scores provide an objective statistical basis for nutritional classification (Anita, 2024; Pujari et al., 2025). However, because these scores are derived through normalization against a reference population, their interpretive validity is inherently sensitive to measurement precision. Even minor deviations in input values may result in clinically meaningful shifts in classification, particularly for children whose measurements lie near diagnostic cutoff thresholds (Grange et al., 2024; Grellety & Golden, 2016).

This statistical sensitivity highlights the critical role of measurement reliability in anthropometric assessment. Errors may originate from multiple sources, including instrument limitations, operator-dependent variability, and inaccuracies during manual data transcription (Diyan et al., 2025; Mocini et al., 2023). Load-cell based weighing systems, for instance, are susceptible to calibration drift, signal conditioning variability, resolution alignment inconsistencies, and observer reading constraints . Beyond device and operator related factors, the continued reliance on paper-based recording systems further compounds the risk of data discrepancies (Chaudhuri et al., 2022). When such inaccuracies accumulate, they may affect not only individual-level clinical decisions but also aggregated public health surveillance and reporting.

In response to these challenges, the integration of Internet of Things (IoT) technology into anthropometric measurement systems has emerged as a promising approach to enhance operational efficiency and data integrity (NAHAL, 2024; Sofie et al., 2025). Microcontroller-based platforms capable of real-time acquisition and wireless transmission allow measurements to be processed, stored, and synchronized digitally without intermediate manual recording. Load-cell sensors integrated with signal conditioning modules and ultrasonic height sensors have been widely implemented in prototype systems aimed at streamlining workflow and reducing transcription errors. Cloud-based databases and web dashboards further facilitate longitudinal growth monitoring and enable rapid retrieval of historical records.

Despite these technological advancements, much of the existing literature remains predominantly focused on hardware architecture and connectivity performance, with comparatively limited emphasis on rigorous validation of measurement accuracy and data consistency. Although digital integration mitigates transcription-related errors, the extent to which sensor calibration, signal processing stability, and system integration collectively influence the reliability of nutritional status classification has not been comprehensively examined. Furthermore, few studies explicitly investigate how quantified measurement error interacts with the inherent sensitivity of Z-score-based interpretation in practical growth monitoring settings. Accordingly, there is a pressing need for an integrated evaluation framework that simultaneously examines instrument performance, quantified measurement uncertainty, and digital data reliability within IoT-enabled anthropometric systems. Such an approach is necessary to clarify whether IoT integration improves workflow efficiency alone or also contributes to more reliable nutritional status classification in routine growth monitoring practice.

**LITERATURE REVIEW**

Existing studies on anthropometric measurement systems have primarily concentrated on improving device-level performance and operational feasibility. In the context of weight measurement, load cell–based systems combined with signal amplification modules have demonstrated acceptable linearity and resolution under controlled laboratory conditions (Rialihanto et al., 2025; Tiffany et al., 2024). However, several investigations report that calibration stability over time and sensitivity to environmental factors, such as surface instability and temperature variation, may introduce measurable drift that affects output consistency(Nalakurthi et al., 2024). While such deviations are often numerically small, their potential clinical implications are rarely quantified in relation to nutritional status classification thresholds. Similarly, height measurement technologies employing ultrasonic or infrared distance sensors have been widely adopted in prototype anthropometric devices (Rofi'i et al., 2025; Wibowo et al., 2025). These systems offer advantages in rapid acquisition and reduced operator dependence. Nonetheless, variations in sensor positioning, child posture, and reflective surface characteristics may contribute to measurement dispersion (Capineri & Bulletti, 2021; Goodloe et al., 2017). While technical validation typically quantifies accuracy using mean absolute error or correlation coefficients compared with reference devices, few studies systematically investigate the downstream impact of these deviations on Z-score determination. The growing adoption of IoT-enabled health monitoring platforms has introduced new opportunities for data integration, longitudinal tracking, and remote accessibility. Recent developments emphasize system architecture, wireless communication protocols, and cloud-based dashboards designed to streamline workflow in community health services. While these technological advancements improve operational efficiency, validation frameworks often prioritize system functionality over comprehensive assessment of measurement uncertainty and its downstream analytical impact.

Beyond instrument performance, several studies highlight the influence of procedural and human factors in routine growth monitoring settings. Inter-observer variability, inconsistencies in child positioning, and differences in measurement timing have been shown to contribute to anthropometric variability (Mwangome et al., 2012). Although digital platforms reduce manual transcription errors, they do not inherently eliminate upstream measurement uncertainty (Chaudhuri et al., 2022). Consequently, improvements in data transmission and storage reliability do not automatically translate into enhanced clinical validity of growth classification.

Notably, few investigations integrate instrument-level error analysis with statistical sensitivity assessment of classification outcomes. Studies that evaluate device accuracy typically report technical performance metrics without explicitly linking them to changes in nutritional status categorization. Conversely, measurement uncertainty is rarely incorporated into public health growth classification analyses. This fragmentation suggests a methodological gap between engineering validation and clinical interpretability. Overall, although digital anthropometric systems have advanced considerably, integration between measurement validation, uncertainty analysis, and classification reliability remains insufficient. An integrated analytical approach that bridges these domains remains insufficiently represented, particularly within routine early childhood growth monitoring contexts.

## RESEARCH METHODS

This study employed an experimental design to evaluate the performance and data integration characteristics of an IoT-based anthropometric measurement system developed for toddler growth monitoring. The evaluation focused on instrument calibration, measurement accuracy, linearity analysis, and digital data integration reliability under controlled testing conditions. Performance evaluations were conducted under controlled indoor to minimize environmental interference. This study did not involve direct measurement of human subjects; therefore, ethical approval related to clinical testing was not required.

The developed system consisted of two primary measurement modules; body weight and body height. Body weight measurement utilized a 30 kg load cell sensor integrated with an HX711 signal amplification and analog-to-digital conversion module. The HX711 provided high-resolution digital output suitable for microcontroller-based processing. Body height measurement was performed using an ultrasonic distance sensor with a maximum detection range of 130 cm, configured to measure vertical distance from a fixed reference point to the measurement platform.

Data acquisition and system control were managed using an ESP32 microcontroller. The microcontroller processed sensor readings, applied basic stabilization filtering, and transmitted measurement data in real time to a web server via Wi-Fi connectivity. Data transmission was triggered per measurement event, ensuring immediate storage without intermediate manual transcription.

The digital infrastructure was implemented using a PHP-based web server connected to a cloud-hosted database. The system enabled structured storage of child identity information, current anthropometric measurement, and longitudinal records. A web-based dashboard was developed to visualize measurement results, display automated nutritional status classification, and present growth trends in graphical form. Z-score calculations were performed automatically within the system using programmed reference parameters derived from WHO growth standards 2006(Mei, 2007). Z-scores were calculated using the WHO LMS method (Sanz Diez et al., 2022), where $Z = [(X/M)^L - 1]/(L\times S)$, with L, M, and S parameters derived from WHO 2006 growth standards. Nutritional categories were generated immediately after data acquisition and stored alongside the corresponding raw measurement values.

Performance evaluation of the weight measurement modules was conducted using certified standard weight as calibration references. Twelve measurement points ranging from 1 kg to 20 kg were tested. Each reference load was measured three times, and the average reading was recorded for analysis. Measurement error was calculated as the difference between the system reading and the reference value (Mukhammad et al., n.d.). Percentage error was computed using the following formula:

$$\text{Percentage error}(\%) = \left[\frac{(X' - X)}{X}\right] \times 100$$

$X = \text{Reference Value}$
$X' = \text{Measured Value}$

To quantify overall deviation magnitude, Mean Absolute Error (MAE) was calculated as:

$$\text{MAE} = \sum |X' - X| \,/ n$$

Where n represents the number of calibration points.

In addition to error analysis, linear regression analysis was performed to assess the linearity of the load cell response across the tested range(Hastawan et al., 2021). The reference weights were treated as independent variables (x), and the corresponding measured values were treated as dependent variables (y). A simple linear regression model of the form y=ax+b was applied. The coefficient of determinant ($R^2$) was calculated to evaluate the strength of the linear relationship between reference and measured value. An $R^2$ value approaching 1 indicates high linear conformity and consistent sensor response throughout the measurement range.

Height measurement validation was conducted by comparing ultrasonic sensor readings with manual measurements obtained using a standard measuring tape. Five reference height points within the operational range were evaluated. Each measurement was repeated three times, and the average value was used for analysis. Error and percentage error were computed using the same formula applied in weight calibration. Linear regression analysis and $R^2$ calculation were similarly performed to examine the consistency of height measurement response.

Data integration performance was assessed descriptively by verifying real-time transmission accuracy, database storage consistency, and dashboard synchronization (Krishnamurthi et al., 2020; Kumar, 2022; Peng et al., 2020). The evaluation confirmed that measurement values displayed on the device corresponded exactly to stored database entries and automatically generated nutritional status classifications.

## RESEARCH RESULTS

The implementation results indicate that the IoT-based anthropometric measurement system for toddlers was able to consistently perform data acquisition, recording, and presentation of body weight and height measurement. Each measurements was automatically stored along with a timestamp in a centralized database, allowing the data to be organized chronologically for longitudinal analysis. The recorded data can be accessed through a web interface and mobile devices in the form of tables, growth charts over time, and nutritional status classifications based on Z-scores, as illustrated in Figures 1 and 2. The graphical visualization demonstrates that the system maintained the correct sequence and continuity of measurement records without data loss, suggesting that the data transmission and storage processes operated reliably and consistently. Overall, these implementation results confirm that the system fucntions effectively as an infrastructure for anthropometric data acquisition and management. Consequently, the generated data are suitable for further analysis, particularly in evaluating measurement accuracy and repeatability.

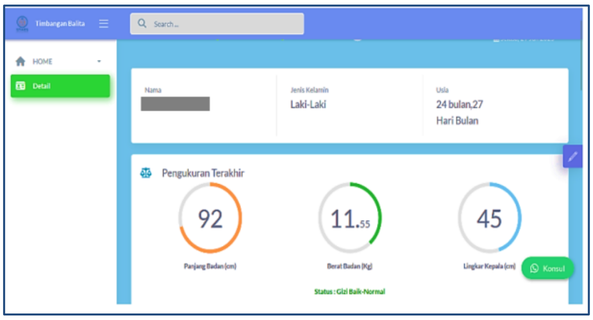


Figure 1. Web Display Of Measurement Results

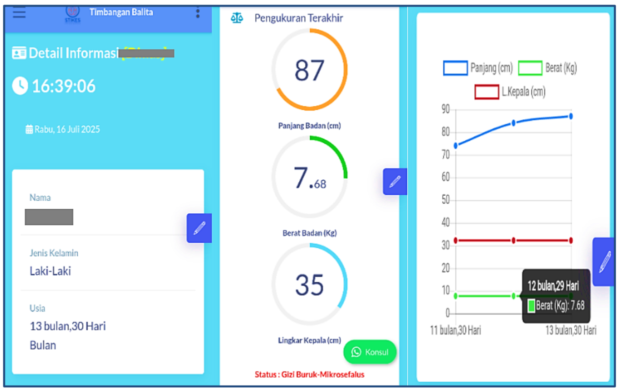


Figure 2. Display Of Measurement Result On Mobile Devices

**Table 1. Load Cell Accuracy Testing**

| No. | Reference weights | Measurement reading (kg) | | | Average | % Error |
|---|---|---|---|---|---|---|
| | | I | II | III | | |
| 1. | 1 kg | 1 | 1 | 1 | 1 | 0% |
| 2. | 2 kg | 2 | 2 | 2 | 2 | 0% |
| 3. | 3 kg | 3 | 3 | 3 | 3 | 0% |
| 4. | 4 kg | 4 | 4 | 4 | 4 | 0% |
| 5. | 5 kg | 5 | 5 | 5 | 5 | 0% |
| 6. | 6 kg | 6 | 6 | 6 | 6 | 0% |
| 7. | 7 kg | 7 | 7 | 7 | 7 | 0% |
| 8. | 8 kg | 8.1 | 8.1 | 8.1 | 8.1 | 1.25% |
| 9. | 9 kg | 9.1 | 9.1 | 9.1 | 9.1 | 1.11% |
| 10. | 10 kg | 10 | 10 | 10 | 10 | 0% |
| 11. | 15 kg | 15 | 15 | 15 | 15 | 0% |
| 12. | 20 kg | 20.1 | 20.1 | 20.1 | 20.1 | 0.5% |

Table 1. shows the body weight evaluation using a load cell sensor; the system demonstrated excellent agreement with the reference

values. Linear regression yielded y = 1.005x − 0.018 with $R^2$ = 0.99997, indicating very strong linear conformity across the calibration range. The regression slope slightly exceeding unity (1.005) indicates minor proportional overestimation at higher loads, consistent with the 0.1 kg deviations observed at selected calibration points. Minor overestimations of 0.1 kg at several points produced a Mean Absolute Error (MAE) of 0.025 kg (25 g), reflecting slight measurement dispersion despite the overall near-linear performance.

**Tabel 2. Height Reading Accuracy Testing**

| No. | Reference | Measurement reading (cm) | | | Average | % Error |
|---|---|---|---|---|---|---|
| | | I | II | III | | |
| 1. | 50 cm | 50 | 50 | 50 | 50 | 0% |
| 2. | 70 cm | 70 | 70 | 70 | 70 | 0% |
| 3. | 90 cm | 90 | 90 | 90 | 90 | 0% |
| 4. | 100 cm | 100 | 100 | 100 | 100 | 0% |
| 5. | 130 cm | 130 | 130 | 130 | 130 | 0% |

Meanwhile, Table 2. shows the results of the height measurement evaluation. The results show consistent values, which indicate excellent repeatability under static testing conditions. Linear regression analysis consequently indicated perfect linear correspondence between measured and reference values ($R^2$ = 1.000), confirming stable sensor response under controlled conditions.

**Table 3. Simulation results of the analysis Weight-for-Height Z-score (WHZ)**

| Case | Age/Sex | Height (cm) | True weight (kg) | Measured Weight (+0.1 kg) | WHZ true | WHZ measured | Classification Change |
|---|---|---|---|---|---|---|---|
| 1 | 18mo/F | 78 | 8.9 | 9.0 | -2.02 | -1.96 | Severe wasting – Moderate wasting |
| 2 | 24mo/M | 85 | 10.5 | 10.6 | -1.98 | -1.92 | Moderate wasting - Normal |
| 3 | 12mo/F | 72 | 7.8 | 7.9 | -3.01 | -2.94 | Severe wasting – Severe wasting (shift within category) |
| 4 | 30mo/M | 92 | 12.2 | 12.3 | -1.02 | -0.96 | Normal (no change) |
| 5 | 20mo/F | 80 | 9.6 | 9.7 | -2.01 | -1.95 | Severe wasting-Moderate wasting |

These findings emphasize that measurement performance should not be interpreted solely through statistical indicators such as MAE or $R^2$, as these metrics quantify numerical deviation but do not directly capture classification stability. The clinical relevance of measurement error is threshold-dependent rather than magnitude-dependent, meaning that its impact is determined by proximity to diagnostic cut-off points rather than absolute size. In growth monitoring practice, the stability of categorical outcomes is equally important. This is particularly relevant in preventive and promotive services, where nutritional classification guides counseling, supplementary feeding decisions, monitoring intervals, and referral considerations. Therefore, even minimal systematic deviations—while technically acceptable—may hold interpretive significance under specific clinical conditions. Integrating awareness of measurement uncertainty into digital anthropometric systems is essential to ensure that technological accuracy translates into reliable clinical decision-making.

## DISCUSSION

The present study demonstrated that the developed IoT-based anthropometric monitoring system achieved high measurement accuracy under controlled conditions. Weight calibration yielded a Mean Absolute Error (MAE) of 0.025 kg alongside an excellent coefficient of determination, indicating strong linear conformity across the tested range. Height measurements likewise showed complete agreement with reference values at the evaluated points. These findings confirm stable instrument-level performance and suggest that, from a technical perspective, the system is appropriate for routine growth monitoring. However, technical accuracy alone does not fully capture the clinical implications of measurement performance within Z-score–based nutritional assessment.

Height measurement results demonstrated perfect linear agreement ($R^2$ = 1.000) and zero observed percentage error under static calibration conditions. These results should be interpreted taking into account the measurement resolution and the system's test configuration. The ultrasonic sensor was configured to report height values in 1 cm increments without decimal precision. Consequently, the smallest detectable change in output was limited to one centimeter. Deviations smaller than the resolution threshold, such as millimeter-level fluctuations, would not be captured in the recorded data. Instead, these values would be rounded to the nearest integer. This discretization effect can produce an appearance of perfect agreement when reference values coincide with integer centimeter points. Furthermore, calibration was performed under controlled indoor conditions using fixed reference distances, thereby minimizing environmental noise, surface instability, and positional variability. Therefore, the absence of observable error reflects the combined influence of output resolution, rounding effects, and controlled testing conditions rather than the absolute elimination of measurement uncertainty. In practical field settings, child posture, movement, and alignment variability are inevitable. Therefore, minor deviations are expected despite favorable static calibration results.

Although the observed MAE appears numerically small, its relevance becomes clearer when situated within the statistical structure of Z-score computation. Z-scores are derived by expressing an individual measurement relative to the median of a reference population and scaling it by the age- and sex-specific standard deviation. Because the calculation directly depends on the magnitude of deviation from the reference median, even minor differences in measured weight can proportionally influence the resulting Z-score value. For example, if the standard deviation for a specific age group is approximately 1 kg, a deviation of 0.1 kg corresponds to a 0.1-unit shift in Z-score. While this shift may appear modest in absolute terms, its clinical meaning is context-dependent. In children whose anthropometric indices lie near diagnostic cut-off points—particularly around −2 SD—small variations may determine whether classification falls within the normal range or indicates undernutrition. Thus, the interpretive consequence of measurement error is not uniform; it is amplified in borderline

Beyond accuracy magnitude, measurement resolution and unit presentation also influence Z-score sensitivity. When anthropometric values are recorded in limited decimal precision or rounded to whole units, implicit rounding errors may occur prior to Z-score computation. In community-based health settings, height is often documented in whole centimeters and weight in one-decimal increments, which may introduce discretization effects. Although each

cases where categorical thresholds function as decision boundaries.

To examine this phenomenon further, a simulation analysis was conducted using five illustrative toddler cases with varying anthropometric profiles using WHO LMS parameters corresponding to the specified age and sex categories. The analysis focused on Weight-for-Height Z-score (WHZ), given its central role in identifying acute malnutrition within maternal and child health services. Each case incorporated sex, height, and body weight parameters, and a systematic deviation of +0.1 kg was introduced to represent potential sensor overestimation. The simulation showed that when WHZ values were substantially distant from diagnostic thresholds—either clearly normal or markedly below −3 SD—the additional 0.1 kg produced only slight numerical shifts without altering nutritional classification. In contrast, when WHZ values were positioned near the −2 SD threshold, small weight deviations resulted in categorical transitions, including shifts from severe wasting to moderate wasting and from moderate wasting to normal status. Although the absolute Z-score changes remained numerically small, the resulting reclassification carries practical implications for clinical management.

rounding instance is small, the cumulative influence of rounding combined with instrument deviation may alter calculated Z-score values in borderline cases. Consequently, both sensor calibration accuracy and output resolution should be considered integral components of classification reliability. Ensuring sufficient measurement granularity is particularly relevant in early childhood growth monitoring, where relatively small absolute differences represent larger proportional changes compared to older age groups.

The integration of IoT technology within the developed system contributed to improved data handling reliability and workflow efficiency. Real-time transmission, automated database storage, and embedded Z-score computation reduced the risk of transcription errors and manual calculation mistakes that commonly occur in paper-based recording systems. From a nursing and midwifery perspective, such digital support may enhance longitudinal growth tracking, facilitate timely identification of growth faltering, and reduce administrative burden in primary care settings. Nevertheless, digital integration does not inherently eliminate upstream measurement uncertainty. The present evaluation was conducted under controlled indoor conditions and did not incorporate variability associated with child movement, positioning inconsistency, uneven surfaces, or environmental disturbances frequently encountered in community health posts. Furthermore, the study did not empirically test classification shifts using real pediatric subjects under field conditions. These limitations indicate that while the system demonstrates strong technical performance, field-based validation remains necessary to confirm its reliability in routine service environments.

## CONCLUSION

The IoT-based anthropometric system demonstrated high measurement accuracy, reflected by near-perfect linearity ($R^2$ = 0.99997) and a low Mean Absolute Error of 0.025 kg. These findings indicate strong agreement between reference and measured values across the calibration range, with only minimal systematic deviations. Despite the small magnitude of error, analytical evaluation suggests that even minor weight deviations (e.g., 0.1 kg) may influence weight-for-height Z-score classification in borderline cases near critical thresholds. This highlights the clinical relevance of measurement precision in pediatric growth assessment, particularly for early identification of undernutrition. Overall, the system exhibits robust technical performance and supports reliable anthropometric monitoring in maternal and child health practice.

Future research should extend system evaluation into real-world maternal and child health settings, incorporating direct measurement of pediatric subjects under routine operational conditions. Simulation modeling may also be employed to systematically examine how specific magnitudes of measurement error influence Z-score transitions across diagnostic thresholds. Comparative studies between conventional manual systems and IoT-assisted platforms would further clarify the practical benefits of digital integration for clinical decision-making. Additionally, refinement of calibration protocols and optimization of measurement resolution may enhance reliability in borderline classification scenarios. Ultimately, technological innovation in anthropometric monitoring should aim not only to improve efficiency but also to safeguard interpretive validity in nutritional assessment. Ensuring alignment between measurement precision, data resolution, and classification sensitivity is essential for strengthening growth monitoring practices within nursing and midwifery care.

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